WILL MILLENNIALS STAY IN CITIES AND TRAVEL WITHOUT CARS?

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WILL MILLENNIALS STAY IN CITIES AND TRAVEL WITHOUT CARS?

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This dissertation and all of my academic achievements are dedicated to my amazing wife and my father, Woo Chan Lee (1939-2014), whose lifelong struggle I truly appreciate.

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SUMMARY

Will millennials stay in cities and travel without cars? To answer this question, this dissertation examines heterogeneity in modality styles and residential preferences in a sample of millennials and members of Generation X in California in 2015. It finds that *both* sociodemographic/ economic characteristics *and* attitudes about various dimensions (e.g., preferred built environments, travel modes, and car ownership) account for the heterogeneous behavioral and choice patterns in the sample. These findings provide insights on the ways millennials may switch their modality styles or residential preferences in response to changes in sociodemographic/economic conditions or attitudes in the coming years. This dissertation highlights the use of latent-class approaches as effective for the identification of heterogeneity in tastes related to the travel behaviors and location choices of millennials. Researchers are advised to apply these approaches to longitudinal analyses. This research also informs planners and policymakers of dynamic changes in the form or share of latent classes in their region.

CHAPTER 1. INTRODUCTION

1.1 Millennials on the Move

Millennials, those who were born from 1981 to 1996 (Dimock, 2018), present travel behavior and mobility choice that differ from preceding generations at the same age. Since the late 2000s, reports have shown that millennials postpone (or some of them appear to forego) the acquisition of a driver's license (Delbosc, 2017; Delbosc & Currie, 2013), own fewer cars on average (Klein & Smart, 2017; Zhong & Lee, 2017), drive fewer miles (Blumenberg, Ralph, Smart, & Taylor, 2016; McDonald, 2015; S. E. Polzin, Chu, & Godfrey, 2014), but instead more frequently use alternative modes such as walking, biking, and public transit (Dutzik, Inglis, & Baxandall, 2014). Academic studies and industry reports also find that, in part because they grew up with advanced information and communication technologies, millennials adopt emerging transportation services such as carsharing and ridehailing more than older cohorts (G. Circella, F. Alemi, K. Tiedeman, S. Handy, & P. Mokhtarian, 2018a; Clewlow & Mishra, 2017).

Mass media has often depicted millennials as a *carless* generation, who have different habits and preferences from older generations, in particular in the early 2010. This topic has been also discussed in the scientific literature (Blumenberg, Brown, Ralph, Taylor, & Voulgaris, 2015; Blumenberg et al., 2016; McDonald, 2015; K. M. Ralph, 2017), even if often mainly as a speculation due to the lack of comprehensive data that could allow to better study the factors affecting millennials' choices. As the US economy has recovered from the economic recession since 2009, the signs of millennials catching up with once-delayed life course milestones have appeared in society (e.g., working full-time or purchasing cars/homes). However, to this date, American millennials still show travel-related choices and outcomes that differ from those of the preceding generations at the same stage in life. On average, older millennials travel more miles by cars in 2017 than during the recession. Still, substantial heterogeneity exists among them: millennials in the low-income bracket increased their car use noticeably, but the other millennials reduced their amount of car travel since 2009 (McCahill, 2018). The gap between the share of age 18-34 living in a car-free household and the same share in the population has not been reduced after the economic recession (Drum, 2018). Although public transit in the US has been losing ridership since the 1940s (S. Polzin, 2016), millennials take more positive views on it (Sakaria & Stehfest, 2013), and their mode shares of walking and biking are larger than those for older cohorts at the same age (McKenzie, 2015). New mobility solutions have been introduced to the market one after another (e.g., bike-sharing, car-sharing, ridehailing, and e-scooter-sharing). Millennials are among the early adopters or frequent users of those solutions (Alemi, Circella, Handy, & Mokhtarian, 2018; Circella et al., 2018a; Smith, 2016), and in part because of the availability of such solutions many millennials live without owning their own cars.

1.2 Factors Accounting For Behaviors and Choices

Studies and reports point to two sets of factors behind these phenomenon, whose effects are difficult to tease out from each other: changes in economies or cultures (Blumenberg et al., 2016; Delbosc & Ralph, 2017; McDonald, 2015). Although the US has been recovering from the most recent recession since 2009, studies find that the crisis still has lagging effects on wages, wealth, and household structure, and these effects appear to be larger for millennials than for preceding generations at the same age (Emmons, Kent, &

Ricketts, 2018). Moreover, rising educational attainment, later formation of an independent household and childbearing, and delayed homeownership are part of long-term societal changes in the US (H. Lee, 2018; Millsap, 2018) in part because of intensifying competition under the global economy and transition to the knowledge-based economy. Last but not least, according to some studies and reports (Davis, Dutzik, & Baxandall, 2012; NAR & PSU, 2015), millennials appear to present values, views, and attitudes that differ from those of preceding generations. They take more pragmatic approaches to car ownership and driving (Delbosc & Currie, 2014; Hopkins, 2016), and they appear to be less materialistic but more supportive of environmental policies and active lifestyles (Davis et al., 2012). Also, with their experience with advanced ICT, they have the flexibility to choose between virtual interactions and face-to-face counterparts with physical trips, and adopt emerging transportation services while not having their own vehicles (Martin, Shaheen, & Lidicker, 2010; Mishra, Mokhtarian, Clewlow, & Widaman, 2017). They are also claimed to prefer urban lifestyles or close proximity to urban amenities (Coutoure & Handbury, 2017; H. Lee, 2018).

1.3 What Are We Missing Here?

In this context, the academic and planning communities still lack an understanding of the fundamental relationships among various factors affecting the travel behavior and mobility/location choice of millennials. *First*, many studies analyze conventional household travel surveys that are available to the planning and scientific community, but usually lack information on individual attitudes and preferences. Thus, their discussions are based on speculations, but not based on the estimates of the effects of attitudes. Although a few studies examined any generational differences in attitudes by conducting in-depth interviews and organizing group discussion sessions, in many cases their samples are small or not representative of the general population (e.g., cases were recruited by convenience/snowball sampling). *Second*, most studies examine various elements of travel-related choices and outcomes rather separately but not in a connected way. As for mode choice, less use of one mode may be compensated by more use of other modes; however, analyses of individual components of travel behavior (e.g. mode choice) cannot detect any trade-off behavioral pattern. Also, one of the fundamental choices that affect travel demand, location choice, has not been modeled properly in the literature. Instead, many studies modeled the built environment attributes as exogenous, which in fact are an outcome of a deliberate choice making process. *Third*, with a few exceptions, the millennial literature does not examine the heterogeneity within and across generations. Given that the millennials are the most diverse generation in the US history (Frey, 2016), it is reasonable to assume that they consist of several distinctive groups with heterogeneous behavioral patterns and preferences. To the extent that this hypothesis holds true, the right question to ask is not whether millennials present different behaviors and choices *on average*, but in which forms and size heterogeneity is present among them and between them and preceding generations, and how likely it would change over time.

1.4 How to Address the Literature Gap?

To address the aforementioned literature gaps, this dissertation takes three approaches: employing a survey dataset that contains attitudes/preferences, analyzing travel behavior and residential location of millennials in conceptually and methodologically rigorous ways, and modeling heterogeneity in behavior and choice within and across generations.

In this dissertation, I employ the California Millennials' Dataset, which was collected with an online transportation survey that contained detailed behavioral and attitudinal questions, and it was administered to individuals living in various parts of California in fall 2015 (N=1,975 millennials and members of Generation X). Compared to the data employed by many other studies, two merits stand out: the comprehensiveness of variables and its representativeness for a target population. First, the survey asked a broad set of questions on various topics such as general attitudes and preferences, the adoption of information and communication technologies, living arrangements and residential location, current travel behavior, past/future life course events, work/school locations, and sociodemographic and economic traits. The survey also asked the level of agreement/disagreement with 66 attitudinal statements on various dimensions of everyday life including travel modes, car ownership, preferred neighborhood types, the adoption of technology, materialistic lifestyles, support for environmental policies, concerns related to climate change, and peer pressure. With the sociodemographic and economic characteristics and attitudes available in the data, this dissertation examines their effects on the travel behavior and location choice of millennials and Gen Xers. Second, with the individual weights available in the data, this dissertation conducts weighted analyses, whose outcomes are representative of millennials and Gen Xers in California in terms of race, ethnicity, presence of children in the household, household income, student/employment status, and sex (Circella, Alemi, Tiedeman, et al., 2017).

This dissertation models the travel behavior and location choice of millennials and Gen Xers with rigorous approaches. For the measurement of travel multimodality, this dissertation employs a set of indicators, which are rarely available in conventional transportation surveys but better capture travel multimodality under its temporary variation. In this dissertation, I only include the *monthly* frequencies of use of various modes, but exclude medium-term mobility choices (e.g., the acquisition of a driver's license, car ownership, transit pass holding, or annual vehicle miles traveled) from the list of indicators. After all, the second group of measures are either (prerequisite) commitment to or consequences of certain modality styles. Regarding the residential location choice of millennials and Gen Xers, this dissertation employs a conceptual framework, which articulates the relationships of individual characteristics and neighborhood attributes in a multi-stage residential choice process. The process defines forms the choice set of individuals, which consists of the actual choice and (unchosen) alternatives (*e.g.,* Census block group) randomly selected within an estimated search radius (i.e., maximum acceptable commute distance) from work/school. By doing so, it studies residential choice using *revealed preferences* of millennials and Gen Xers in real, constrained choice situations.

This dissertation models unobserved heterogeneity in modality styles and (revealed) residential preferences in the population by employing two latent-class models: a latent-class cluster analysis for travel multimodality and a latent-class choice model for residential choice. Two reasons for the use of the latent-class models: First, the use of a specific (birth) year as the threshold that identifies two generations is inherently arbitrary, and this approach estimates *average* differences in behavior and choice between the two generations, which may be of less interest to planners and policymakers. If the average differences between millennials and Gen Xers are in fact, the manifestation of differences in the composition of unobserved groups with heterogeneous lifestyles and choices within each generation, the average differences will misinform planning and policy. After all, they are underestimates for one group and overestimates for another group. Second, given that millennials are the most diverse cohort in the US history (Frey, 2016), they are likely to present heterogeneous lifestyles and preferences within themselves, which studies, reports, and media speculated with anecdotes and aggregate statistics (Kolko, 2016, 2017), but did not yet examine thoroughly.

1.5 The Structure of This Dissertation

This dissertation is organized as follows. Chapter 2 explores the various factors that academic research and industry reports list as factors affecting the behaviors and choices of millennials. Chapter 3 serves three purposes: First, Chapter 3 introduces the conceptual framework on which this dissertation builds, in particular regarding travel multimodality and residential location choice of millennials vs. older adults; Second, Chapter 3 discusses the research methods and explains the two latent-class approaches employed in this dissertation: latent-class cluster analysis for travel multimodality and latent-class choice modeling for residential location choice; Third, Chapter 3 presents the details of the main dataset, the California Millennials Dataset, and the descriptive statistics for its key variables. Chapter 4 presents the heterogeneous modality styles in a commuter sample of millennials and Gen Xers (n=1,070). Then, latent classes, associated with the modality styles, are examined in terms of individual profiles, their changing shares by generation, and implications on research and practice. Chapter 5 explores the heterogeneous residential preferences among a sample of independent millennials and Gen Xers (n=729). In Chapter 5, I also examine latent classes, associated with the residential preferences, in terms of individual profiles, their changing shares by generation, and implications and suggestions.

Chapter 6 revisits the main findings of this dissertation and provides directions for future research and suggestions for planning and policy, and Chapter 7 summarizes the findings and provides directions for future research.

CHAPTER 2. LITERATURE REVIEW

Who are today's young adults (i.e., Generation Y or millennials)? According to the Pew Research Center, which defined millennials as those born from 1981 to 1996 (Dimock, 2018), they are less attached to certain political and religious groups, are digital natives, have more racial diversity but low social trust, experience economic hardship (though they keep optimistic view on future economy), and hold different views about major social issues compared to their older cohorts, generation X and baby boomers (Taylor, Doherty, Parker, & Krishnamurthy, 2014). For example, of the 617 millennials among the total 1,821 adults in the survey, 81 percent were on Facebook, their median number of Facebook friends was 250, and 55 percent of all the young adults in the survey posted “selfie” on any social media sites, though many of their older counterparts did not recognize what the term selfie refers to. Certainly, information and communication technology (ICT) and electric devices, which help people connected (i.e. being “on the air”) to friends and colleagues anytime anywhere, are the last thing that millennials need to get accustomed to (Taylor, Doherty, et al., 2014).

Today's young adults suffer more from economic burdens in the form of student loan debt and unemployment. millennials are the most educated generation with about one third of them having at least a four-year college degree (Taylor, Doherty, et al., 2014). As society depends more on knowledge-based industries, less-educated young workers with at most the high school degree are more likely to receive low wages and to be at greater risk for unemployment (Fry, Parker, & Rohal, 2014). However, higher education comes with expensive costs, and among today's graduates with Bachelor’s degree, two thirds have substantial student loan, with average of USD 27,000, whereas only the half of college graduates had any debts whose average was USD 15,000 in the 1990s (S. Baum, 2013). Though economic hardship started to increase before the recent recession, millennials, especially older ones, suffered more, because it was the time when they first entered the job market when the US economy was in recession. Older teenagers and young adults showed higher unemployment rates than the average in the US; 16.1percent for 16 to 19 years, 9.4percent for 20 to 24 years, 5.3percent for 25-34 years, 4.0percent for 35-44 years, and 3.5percent for 45-54 years in December 2015 (BLS, 2018).

An analysis based on the US Census Current Population Survey in 1963, 1980, 1998, and 2014 revealed that Generation Y is a more diverse group in race and ethnicity with only 57 percent of the Caucasians, while Generation X and Baby Boomers had 66 percent and 77 percent among them when they were 18-33 age old in 1998 and 1980 respectively (Fry, Igielnik, & Patten, 2018). Marital status presents a stark contrast between millennials and preceding generations; only 24 percent of millennials were married in 2014, whereas 38 percent of Gen Xers and 49 percent of Boomers were in marriage when they were 18-33 age. Though one reason for such late marriage is heavier economic burdens on Gen Y, another is attributable to values and beliefs that differ from those of older birth cohorts. Based on 2012 Pew Research Center Religion and Public Life Project Survey, only 58 percent of millennials replied that they believed in God with absolute certainty, while 69 percent of Gen X and 73 percent of Boomers answered so (Taylor, Doherty, et al., 2014). Another survey by Pew Research Center in 2014 found that today's young adults support gay rights more, but show less support for patriotic people, religious people, or environmentalists, compared to Gen X and Baby Boomers (Taylor, Doherty, et al., 2014). They may stick less to traditional lifestyles, which their parents followed as social and personal norms, such as getting married, raising kids, and buying suburban homes at certain ages in life.

2.1 Factors Explaining Millennials' Travel Behavior

In this context, a critical question is how millennials' characteristics are connected to different travel patterns. In Figure 1, Blumenberg (2014) provides eight potential causes for millennials' travel behavior: weak economy, auto costs, technology, demographic changes, residential location preferences, cultural differences, regulatory changes for getting driver's license, and availability of alternative travel modes. Among these, this dissertation focuses on four factors: economics, values and preferences, the adoption of Information and Communication Technology (ICT) solutions for travel and other activities, and residential location choice. After introducing key findings and unanswered questions in the literature, three shortcomings are identified: the lack of qualitative variables, incomplete conceptual frameworks, and less attention to heterogeneous preferences in the sample.

<u>Economic</u>	<u>Auto Costs</u>	<u>Technology</u>	<u>Demographic Change</u>
• Recession • Unemployment 	• Gasoline • Auto insurance • Driver's education • Auto repairs • Other fees	• Communication technology • Transportation technology (Über)	• Delayed marriage • Fewer children • Boomerang 
<u>Residential Location</u>	<u>Cultural</u>	<u>Regulatory Changes</u>	**<u>Alternative Modes</u>**
• More likely to move to and live in cities	• Environmentalists • Less materialistic 	• Graduated Driver's Licensing • Texting while driving laws	• **Better transit** • **Improved infrastructure for walking/biking**

Figure 1 Factors explaining millennials' Travel Behavior (Blumenberg, 2014)

2.1.1 Economic Factors

The millennial literature includes the present economic hardship among the most critical factors affecting the travel behaviors and mobility choices of millennials (Blumenberg et al., 2016; Garikapati, Pendyala, Morris, Mokhtarian, & McDonald, 2016; Klein & Smart, 2017; Manville, King, & Smart, 2017; McDonald, 2015). However, as for the extent to which temporary economic struggles account for the behaviors and choices of millennials, especially compared to changes in cultures, preferences, and the role of emerging technologies, transportation researchers appear to provide diverging interpretations: i.e., some emphasize economic aspects more, while others do so less (Delbosc & Ralph, 2017). After all, the understanding of the contribution of various factors surrounding millennials needs to guide our decisions on transportation planning/policy and investments on infrastructures in coming decades.

While conducting a pseud-panel analysis with repeated cross-sectional data of 1995, 2001, and 2009 NHTS, one study presents two competing theories explaining the low automobile dependence of millennials: (1) they work less, study longer, and delay major life course events, and (2) they may have different values and beliefs, and pursue technological solutions for travel needs (McDonald, 2015). In her attempt to tease out the effects of the two sets of factors, McDonald hypothesizes that, if the economic theory well explains less driving but more use of alternative modes by millennials, at least a subgroup of millennials, who transition to full adulthood (e.g., work full-time, get married, or raise a child) would show similar travel patterns to older birth cohorts when they were young in previous surveys. However, she finds it is not the case. In fact, she showed that changes in demographic and economic characteristics among millennials account only for a small portion of the reduction in car use from 1995 to 2009. Instead, after teasing out the period effects that apply to all birth cohorts, she reports a substantial portion of variation in vehicle use remains in the model. McDonald interprets this portion as a supporting, though indirect, evidence for cultural differences of millennials from preceding generations.

Blumenberg and her colleagues apply a similar approach to that of McDonald to the past several National Personal Transportation Survey (NPTS) and NHTS data from 1990 to 2009, but they interpret their results quite different ways (Blumenberg et al., 2016). According to them, the mobility choice of a certain age group at a given point in time is decomposed into three components: ***Life Cycle*** effects refer to the part of travel patterns explained by individuals staying in certain life stages, and these effects apply to individuals of any generation as long as they stay in the same stage. Employment, marriage, childrearing, and retirement are typical examples, and life cycle effects do not follow individuals once these individuals pass onto the next stage; ***Period Effects*** capture the part of travel patterns explained by specific events taking place in society and experienced by all individuals at the moment (e.g., an economic recession). These affect all individuals at one point in time, but not those at different points in time; ***Cohort Effects***, the main focus of the millennial literature, indicate the part of travel patterns attributable to individuals belonging to certain birth cohorts, and they are assumed to follow those birth cohorts over time. With this framework, Blumenberg and her coauthors show that life cycle effects (e.g., employment) prevail, suggesting that as millennials catch up with delayed life course events, they would behave in similar ways as preceding generations did in the past (e.g., suburban homes and auto-dependent lifestyles).

Just as aforementioned studies present conflicting views on the sources of low travel demands by millennials, other studies attribute the low vehicle ownership by millennials to different factors. Klein and Smart (2017) examine the car ownership levels of several birth cohorts with eight waves of the panel study of income dynamics that followed the same individuals from 1999 to 2013. While they find that millennials own fewer vehicles on average than older birth cohorts, economically independent millennials, who do not live with their parents, own similar or slightly more vehicles than expected given their incomes and wealth. Thus, Klein and Smart conclude that the low vehicle ownership by millennials is mainly attributable to their current economic distress, and once they gain economic resources, although at later points in time than preceding generations, their level of vehicle ownership would not differ much from older birth cohorts.

In contrast, Zhong and Lee (2017) present that household car ownership has already been declining since 2000 in the Puget Sound Regional Council, which covers part of the Seattle metropolitan area. With the combined data of nine-wave panel (from 1989 to 2002) and two repeated cross sections (2006 and 2014), their count models reveal that households headed by young adults from 25 to 34 own fewer vehicles. Moreover, this age group as of 2014 owned even fewer vehicles on average all else being equal, and the members of this age group living in more compact neighborhoods owned far fewer vehicles in later years, 2006 and 2014, suggesting that with land use planning and policy planners and policy makers can leverage the social trend of lower vehicle ownership in areas in which alternative travel modes are more viable.

2.1.2 Values, Perceptions, Attitudes, and Preferences

Another group of variables related to young adults' travel behavior is their seemingly different values and beliefs compared to older cohorts. They are often claimed to be less materialistic, more supportive for environmental issues, more likely to live at urban cores or suburban dense neighborhoods, more concerned with diet and physical exercise, and less likely to adopt traditional family-centered lifestyles (Blumenberg, 2014).

A group of studies based on focus groups or in-depth surveys have been conducted for Gen Yers' current travel patterns and their perceptions on and desire for car ownership. Puhe and Schippl held three focus group meetings with 90 young adults in their 20s in Karlsruhe, Budapest, and Copenhagen (Puhe & Schippl, 2014). They found that their meeting participants had "pragmatic attitude[s]" toward travel modes: i.e., these young adults preferred modes that provide "flexibility, convenience, and low price", but not always cars. These participants also expressed positive reactions to policies for the promotion of alternative travel modes.

Simons et al. (2014) conducted a qualitative analysis by having six focus group meetings with 19 students (age 21 ± 1.1) and 17 workers (age 23 ± 1.5), most of whom studied or worked in the City of Antwerp, Belgium. With the grounded theory approach, they developed categories and subcategories affecting young adults' mobility choice. Three major sets of factors, personal, social, and physical, are found varying levels of impacts on travel behavior. While valuing autonomy, these young adults preferred cycling to public transit because of the limited destinations, fixed operating hours, or infrequent schedules of transit services. As expected, social influence was another critical factor influencing their mobility choice: *"I don't mind cycling somewhere when we go with a group of friend.", "Transport choice is dependent on my partner. If he doesn't come along, I mostly go by bike, because I want to cycle as much as possible. But my partner always wants to go by car, even if it's nearby, because he has a company car."* (Simons et al., 2014). However, in contrast to the popular notion that millennials do not want a car, most of non-owners (who were students) showed plans for buying a car, and owners confessed they came to rely heavily on cars after buying them: *"I have only had my driver's license for one year and before that I did everything by bike. But now I have a car and it stands there and that is a luxury. And now I always use my car. I almost miss cycling a bit."* (Simons et al., 2014).

Delbosc and Currie (2014) conducted a qualitative study project by employing an online discussion forum, in which 33 young Australians, aged 17 to 33, participated for a week. First, these participants were asked to evaluate various factors affecting their travel behavior and mobility choice, and later, they were “prompted” by researchers consider three attitudinal constructs, the status of a car, the use of ICT services, and environmental concerns. Although the participants did not relate car ownership as a symbol of status or success, they do accept it as a means with which to claim responsibility, maturity, or adulthood. These participants also think electronic communications as complementary, not substitutive, to face-to-face interactions and physical trips. Unexpectedly, environmental concerns were not a factor for any participant to affect their driver’s license, car ownership, or driving. While this study provides a rare and invaluable empirical test of the role of specific attitudes on travel behavior, its sample is too small and non-representative for the generalization of its findings to other areas.

Haustein, Klöckner, and Blöbaum (2009) explored the three different types of the past and present “socialization” or personal interactions on the norms, habits, and intention of young adults related to driver’s license and driving. With the data collected online from 2,612 students from a German university, they estimated structural equation models, in which the nature of discussion with parents about environmental impacts of driving at the age of 15, perceptions about the acquisition of a driver’s license and driving at the age of 18 (all cases in the final sample are with a driver’s license and access to a car), and the extent to which students’ peer group consider alternative modes. Their models reveal that these three socialization constructs affect personal and social norms, the habits of car use, and travel behavior. As a conclusion, this study suggests to expand the scope of policies and programs so that the key socialization process can be intervened for the promotion of sustainable travel behavior.

Hopkins (2016) examined the extent to which environmental concerns or the awareness of negative impacts of private motorized travel modes affect the intention or actual practice of learning to drive, driving, and car ownership with the 51 interviews of young adults between age 18 to 35 in New Zealand. With the combined theoretical framework of the theory of planned behavior and the social practice theories, she explored underlying values, perceptions, and social, economic, and built environment contexts that account for mobility choice and travel behavior of the interviewees. In agreement with previous studies on similar topics (Delbosc & Currie, 2013), her qualitative analyses present that many interviewees understand having a driver's license represents *desired* personal characteristics (e.g., maturity, responsibility, perseverance, reciprocity, adulthood, and employability), while they also attach to automobiles such traditional values as freedom and independence to lesser extent. Interestingly, environmental concerns appear to affect modal choice more than the intention or practice of learning to drive, and the built environment attributes such close proximity to friends or school/work disincentivize car-dependent behavior.

With a longitudinal design, Deka (2018b) compared the perceptions of five generations, Silent Generation, Great Generation, baby boomers, Generation X, and millennials, on the public spending on cities, public transit, and highways. He analyzed data from the General Social Survey (GSS) of the United States from 1984 to 2016, a nationally representative repeated cross-sectional data, which allow him to explore any shifts in the perceptions among those generations when they were at the same age. GSS asked whether individuals perceived the level of government expenses on public goods and services too much, right, or too little. As the variables of interest, Deka used three perception questions on “solving the problems of big cities”, “mass transportation”, and “roads and bridges.” While controlling for personal and household characteristics, his final results present that the perceptions of millennials on the public spending on cities and public transit do not differ from those of the preceding generations. In comparison, millennials tend to perceive government spending on highways too much compared to Silent and Great Generations (but not to baby boomers and Generation X), that they may be less supportive of expanding the capacity of existing roads or building new infrastructures for automobiles. Interestingly, Deka found separate effects of educational attainment and a neighborhood type at age 16, suggesting the US may see more urbanites in coming decades at least because of sociodemographic shits and reverse trends in location choice.

Okulicz-Kozaryn and Valente (2018) also analyzed data from the General Social Survey from 1972 to 2016 to examine any longitudinal change in the relationship between subjective well-being (SWB) and the place of residence (e.g., urban, suburban, or rural). As for SWB, the literature finds that urban residents are less happy than suburban, or even rural counterparts, because of negative aspects of urban lifestyles such as high crime rates, concentrated poverty, congestion, and pollution. This correlation between SWB and the place of residence, or so-called “the urban-rural gradient of happiness”, becomes more pronounced between the largest metropolitan areas and its hinterlands (e.g., New York, Philadelphia, London, and Toronto). In this context, Okulicz-Kozaryn and Valente reveal that the gap in SWB between urban and rural residents has been closing since the 1970s, and when it is examined separately for generations, urban millennials are even happier than suburban or rural millennials compared to preceding generations when they were at the same age. Interestingly, the gap is the largest among Lost/G.I. Generations, and it decreases for following generations. As for underlying causes for such patterns, social and economic trends in the past decades such as the urbanization of the population and disinvestment or economic decline in rural areas in the US appear to play a role in shifting the urban-rural gradient. Still, millennials, often claimed to be an urban generation, seem to present unique residential preferences (and "lower travel proclivity" (Mokhtarian & Pendyala, 2018)), while the duration during which their preferences would last in the future is an open question.

Tilley (2017) developed a comprehensive framework in which three sets of factors affect the mobility choice and travel behavior of the population in a given point in time: period-specific factors, longer-term societal changes, and cultural factors. Although not mutually exclusive with many interactions among them, the sets of factors in her framework help researchers identify diverse sources of change in mobility patterns in the population as a whole and in each birth cohort in specific. As for the cultural factors, Tilley lists longitudinal changes in several dimensions: social and family relations, the role of genders, residential location choice, and mobility cultures. Among these dimensions, mobility cultures refer to values, perceptions, and preferences for certain travel patterns, which differ from generation to generation, and transportation planning and policies influence and be influenced by them. For example, government subsidies on public transit and active modes, the congestion charging in London, information campaigns of the benefits of active modes and the risks of sedentary lifestyles are often claimed to form mobility cultures (and also be formed by them). With the framework, she revisited her previous analyses on the United Kingdom National Travel Survey from 1995 to 2008

(Tilley & Houston, 2016); however, lack of relevant variables did not allow her to specify the size of effects by various factors including perceptions and preferences on changing mobility patterns in the UK.

2.1.3 Information and Communication Technology and New Transportation Services

Although some might view the use of information and communication technology (ICT) as a strategy for the reduction of travel demand (e.g. telecommuters drive fewer miles because of saved commute trips), scholars have suggested that the adoption of ICT has multifaceted effects on travel demand. In her seminal paper on the conceptual framework of the effects of ICT on travel demand, Mokhtarian (2004) suggests that not only substitution but also complementarity, modification, and neutrality (i.e., no effects) are likely to take place. Moreover, the effects of ICT use on travel demand may vary by trip purposes, and both elasticity of own demand (e.g. telecommuting decreases commute VMT) and cross-elasticity between trips with different purposes (e.g. telecommuting induces social/leisure trips due to an unused travel time budget) need to be considered. In the meantime, different generations may respond to ICT in different ways. Generation Y and older cohorts may have different patterns in telecommuting, online-shopping, and social media use, the three major mechanisms in which ICT use may affect travel demand. As Circella and Mokhtarian (Circella, 2017; Circella & Mokhtarian, 2017) point out correctly, the key factor is to understand the reasons for which individuals choose technological solutions instead of conventional physical trips. Values, perceptions, knowledge, experiences, and preferences would make substantial differences between different age cohorts and within the same generation regarding ICT effects on travel demand.

According to Circella and Mokhtarian (Circella, 2017; Circella & Mokhtarian, 2017), three main causal paths from ICT adoption to travel demand have been analyzed in the literature: telecommuting, online-shopping, and social media use. To date, studies with a specific focus on ICT effects on millennials' travel patterns are few. The lack of reliable measurements in surveys is one of the main challenges. It may be the case that not only the overall amount of ICT-enabled mobile device and SNS use but also the understanding and timely use of location-based service (e.g. Google maps and smartphone apps for local transit real-time information) make real differences. Moreover, a more comprehensive framework is not yet applied. For instance, peer effects (i.e. how much individuals are affected by their peers in decision making) may explain the difference in travel choices among people with similar use patterns of mobile devices and online social network services (SNS).

With the advancement of ICT and the rising market penetration of smartphones and mobile internet-enabled devices, a unique form of economy has been formed to serve diverse travel needs. So-called “sharing economy” refers to a wide range of economic transactions that make one to use goods and services without owning them, and is central to new mobility options. Though the concept of sharing a physical equipment with others has long existed, for example, taxis and hotel rooms, what makes sharing economy or collaborative economy unique is that sharing *excess capacity* of others becomes much easier and more convenient (Maycott, 2015): e.g. Uber and Lyft connecting non-professional drivers to passengers, and Airbnb helping people share unused rooms of their houses. At the core, ICT enables real time search, immediate request and communication between buys and sellers, and online transactions, all of which can be completed in seconds via smartphone apps on hand. In this context, sharing a means of transportation, not buying and keeping it at home, has become popular among millennials in part because many of them cannot afford a car even if they want one (Rebell, 2015) and they are presumably more open to the idea of sharing with others (or less averse to doing so). In transportation, fleet-based or peer-to-peer carsharing (e.g. Zipcar), dock-based or dockless bike sharing (e.g. Citi bike in NYC), and on-demand ridehailing services (e.g. Uber and Lyft) are among widely known and accepted models, and more disruptive technologies and services are expected to arrive (e.g., Mobility-as-a-service). These new mobility options are readily available to millennials, while preceding generations did not have access to when they were young. Note that millennials are more likely to live in urban or dense areas in metropolitan areas for various reasons, and new mobility options are more available in those areas (Hallock & Inglis, 2015). Moreover, mobile internet-enabled devices, which young adults are reported to value more than cars (Zipcar, 2013), make the use of new mobility options more convenient in terms of checking availability, requesting/reserving, and paying for it.

2.1.3.1 Carsharing

Studies suggest a few mechanisms with which new transportation services change the mobility choice of millennials. Carsharing provides an access to cars based on individuals' needs, so those with irregular or lesser needs can postpone buying a car, reduce the number of household vehicles, or forego buying a car. Martin et al. (2010) estimated effects of carsharing on households' vehicle holding by analyzing a large sample of the carsharing member in North America (n=6,281). They found that the average number of household vehicles reduced from 0.47 to 0.24 after individuals joined membership-based carsharing programs, which is the equivalent of 9 to 13 vehicles being removed from the road for each addition of a carsharing vehicle. With the same data set, another study examined the cross-mode effects of carsharing and revealed that in the sample, *more* members of carsharing programs tended to increase their use of public transit, walking, biking, and carpooling, although individuals varied in their use of other travel modes (Martin & Shaheen, 2011).

Mishra and his colleagues presented the substantial effects of joining to carsharing on household vehicle holdings by analyzing a subsample of the 2010-2012 San Francisco metropolitan travel survey (Mishra et al., 2017). Unlike studies based only on the members of carsharing programs, who differ significantly from non-members, this travel survey recruited all types of residents within the San Francisco metropolitan area, regardless of the use of carsharing services. Note that a simple comparison of carsharing members to non-members cannot produce unbiased causal effects because people choose whether to join a carsharing program for various reasons. Thus, those with less desire to own cars may have chosen to be carsharing members, and in this case, the effects of carsharing is confounded by the intention of less car use. In response, Mishra and his colleagues first controlled for individuals' propensity of being a carsharing member based on observable characteristics of household income, residence type, built environment, and other sociodemographic variables. Even after controlling for self-selection, they still found that the members owned fewer vehicles than non-members, and the differences between two groups of residents increased as the propensity of joining carsharing programs rose; i.e. when comparing two groups (members vs. non-members) with higher propensity scores, their gap in household vehicle holding was larger than the gap between two groups with lower propensity scores.

2.1.3.2 Ridehailing

As transportation researchers pointed out (Clewlow & Mishra, 2017; Vine, Latinopoulos, & Polak, 2013), the main challenge for the analysis of emerging mobility options or transportation services is that the industry evolves much faster than the pace in which the academic community conducts research projects for the understanding of changing travel behavior and suggestion of policy implications. As a result, we have many industry and consulting reports with descriptive statistics, but not many rigorous peer-reviewed research articles that controlled for confounding factors and attempted to estimate "true" causality. One exception is those studies on the effects of carsharing, which researchers have been extensively studied since the early 2000s in part because it has been slower in transformation of its services and business models than ridehailing services.

Clewlow and Mishra (2017) explored the effects of ridehailing services on vehicle ownership and the use of other travel modes with a sample of individuals residing in seven major metropolitan areas in the US. In a self-administered online survey, the majority of respondents (91%, weighted) reported they *did not change* their level of vehicle ownership, which is higher that the estimates of those studies with non-representative samples (Hampshire, Simek, Fabusuyi, Di, & Chen, 2018). Although the portion of *car-shedding* respondents was not substantial, when the entire sample is divided by their frequency of using ridehailing services, the more individuals used ridehailing services, the more they disposed a car or kept not having a car. Also, a sizeable portion of respondents (29%) reported to reduce personal vehicle use since the adoption of ridehailing services. For the effects on use of public transit and active modes, the behavioral patterns of respondents varied by mode: while respondents rode commuter rail and walked more, they reduced use of buses, light rail, and biking. Also, to a related question of "what mode would you use if ridehailing services were not available?", responses are heterogeneous ranging from reducing trip frequencies to carpooling or driving. Since their analyses are descriptive, but not controlling for confounders, diverse patterns of behavioral changes suggests further research to take into account the specific contexts of ridehailing trips: e.g., individual, trip, and urban form characteristics.

In a series of analyses, Alemi and his colleagues explored the adoption, frequency of use, and impacts of ridehailing services among millennials and members of Generation X in California as of fall 2015. Similar to previous studies (Rayle, Dai, Chan, Cervero, & Shaheen, 2016), they find the users of ridehailing services are younger, highly educated (i.e., at least with a Bachelor's degree), employed or studying at school, in higher-income households without children, and living in dense urban neighborhoods in which such services are readily available (Alemi, Circella, Handy, et al., 2018). Moreover, they also find that ICT use for non-transportation purposes (e.g., frequent use of e-shopping and online social network services) increases the odds of using ridehailing services, supporting the claim that "technological savviness" of young and older adults plays a critical role in the adoption of emerging transportation services. Interestingly, *recent movers* are more likely to use such services suggesting they are prone to reevaluate and break transportation habits, or they have more active lifestyles in terms of relocation and trial of new things. As for the frequency of use of ridehailing services, they reveal that the set of individual/household characteristics affecting the frequency differs substantially from that affecting the adoption, suggesting lifestyles and preferences matter more in this context (Alemi, Circella, Mokhtarian, & Handy, 2018). As for the travel mode that ridehailing users would have chosen in the absence of those services, many reported not only motorized modes such as driving and taxi, but also alternative modes including walking, biking, and public transit, suggesting heterogeneous substitution patterns in the population, which depend on individual, trip, and the built environment characteristics (Alemi, Circella, & Sperling, 2018).

2.1.4 Residential Location Choice

The transportation and land use interaction literature has found that travel patterns are a function of characteristics of both individuals (e.g. socio-demographics, economics, and attitude/preference) and their surrounding environment (e.g. the built environment and the level of service by different modes), which in fact is a choice of individuals. Thus, the joint decision of residential location and travel behavior can be modeled in multiple stages. For instance, individuals choose their residence first and then make related choices for everyday trips *given* their chosen residence. In the context of millennials, a critical question for the first stage is if they choose to live in cities because of affordable rental markets and greater job access or preferences for non-motorized travel and urban lifestyles. These two competing explanations are a variant of economy versus culture theories in the previous debate (Deka, 2018a; Delbosc & Ralph, 2017).

A group of transportation researchers in the University of California at Los Angeles (UCLA) attempt to understand the location choice of millennials and identify any systematic difference from that of older birth cohorts. With factor- and cluster-analysis techniques, they first developed a neighborhood typology consisted of seven distinctive types for the all census tracts in the US (Voulgaris, Taylor, Blumenberg, Brown, & Ralph, 2017). With the typology as an explanatory variable, they examined the extent to which millennials are likely to be car-oriented or carless (K. Ralph, 2016; K. Ralph, Voulgaris, Taylor, Blumenberg, & Brown, 2016). Although young adults are more likely to live in urban neighborhoods without access to cars, they presented that the share of young adults in suburban or rural urban neighborhoods is much larger than that in urban counterparts, which challenges the popular notion of urban millennials in the media. Still, there is discernible variation within millennials. If young adults get married, raise children, employed, or fall in the highest income quintile, they are more likely to live in suburban neighborhoods, and vice versa. Though these analyses do not claim causality in part because of lack of attitude/preference variables, in their studies, millennials appear to behave in a similar way to their parents, as they experience key events in life stages (Blumenberg et al., 2015). However, the extent to which young adults will give up their current urban lifestyles is not clear, and cannot be answered with cross-sectional analyses.

Raymond and Dill (2015) focus on a subset of millennials who experience more flexibility in location choice, millennial first-time homebuyers. This group of young adults are deemed less financially constrained because of supportive policies and subsidies. As a result, they are expected to choose residential locations *relatively more* by their preferences. Using the New York Federal Reserve Back Consumer Credit Panel (NYFRB-CCP), they present the descriptive statistics that younger first-time homebuyers tend to choose neighborhoods closer to the Central Business District (CBD) of large metropolitan areas than their older counterparts. Interestingly, while the difference between the two groups decreased during the recession, it has increased after the recession. By controlling for the risk score of individuals (a measure based on the credit score), the total balance of the first-time mortgage, the total balance of any student loans, and year and MSA fixed-effects, they find that from 2006 to 2014, age (from 25 to 60) has a *negative* effect on the distance between the first-time buyers' homes and the city centers. Unlike studies by the UCLA group, this study claims that urban lifestyles of millennials are not only limited to a dozen of the biggest metropolitan areas. However, it is unclear how long young adults of 25 to 34 will stay in cities after they buy homes in urban neighborhoods. Some of them might move to suburbs once their child gets old for schools.

To test the hypothesis that preferences for urban lifestyles have millennials to choose cities, Deka (2018a) examined the county-to-county domestic migration patterns in the US by two birth cohorts, millennials (25-34 as of 2013) and older adults (45-64 as of 2013). With the US Census American Community Survey 5-year estimate of 2011-2015, his analyses presented that urban counties (those with a larger share of the population inside urban areas, a higher density, a smaller share of single-family detached houses, a larger share of commuting by walking and public transit, but a smaller share of commuting by driving) attracted more millennial in-migrants and vice versa. Interestingly, he also finds that the effects of urban counties on millennial in-migration do not differ from that on older adult in-migration, which suggests heterogeneous location preferences among young and older adults.

For the 20 largest metropolitan areas in the US, Lee and his colleagues (B. Lee & Lee, 2017; B. Lee, Lee, & Shubho, 2018) explored the relationship between urbanism factors and the net migration of several birth cohorts, such as millennials, Gen Xers, and baby boomers. At the US Census tract level, they find that those census tracts inside the central city, with closer to the central business district (CBD), with more compact development patterns, with richer consumption amenities, and better served in terms of alternative travel modes gained more millennial in-migrants in net, while those census tracts did not do as well in terms of attracting older birth cohorts. They also examined the historical trends of the same relationships from 1980 to 2010 and found that early Gen Xers differed more from baby boomers in the 1990s in their migration patterns than the extent to which late Gen Xers and millennials together did so from the early Gen Xers in the 2000s, suggesting that the urban living of millennials in the present is in part driven by their stronger preferences for cities (Couture & Handbury, 2017).

2.1.5 Literature Gaps

This chapter introduces key factors in the millennial literature accounting for their unique travel patterns: temporary economic hardship, attitudes and preferences, use of ICT and emerging transportation services, and urban lifestyles. In doing so, several gaps are identified. First, lack of qualitative variables such as attitudes and preferences prevents researchers to examine the separate contribution of economic and cultural factors. As a result, many studies present interpretation based on correlation patterns, or speculations. As for perceptions and preferences, studies employ focus-group interviews or snow ball sampling, which cannot be generalizable beyond their specific samples. In addition, while emerging transportation services have gain popularity by millennials, technologically savvier and living more in dense cities, academic research has not caught up with the innovation and transformation of the industry that provide such disruptive services in part because of new challenges in data collection. Last but not least, even though daily travel behaviors are affected/constrained by residential location, many studies do model it as a part of choice decision, but treat it as exogenous to mobility decisions.

CHAPTER 3. CONCEPTUAL FRAMEWORKS, METHODS, AND DATA

3.1 Conceptual Frames

This chapter introduces two conceptual frames, one for travel multimodality and the other for residential preferences. The analytical methods for the two topics are presented in greater detail in Chapter 4, and their results and implications are discussed in Chapters 6 and 7 respectively.

3.1.1 Travel Multimodality

With the frequencies of use of various travel modes, this dissertation examines the various forms of multimodal travel behaviors (i.e., travel multimodality). While studies do not agree about how multimodality should be measured (Buehler & Hamre, 2014; Circella, Alemi, Berliner, et al., 2017; Diana & Mokhtarian, 2009; Molin, Mokhtarian, & Kroesen, 2016; Nobis, 2007; K. M. Ralph, 2017; Scheiner, Chatterjee, & Heinen, 2016; Vij, Carrel, & Walker, 2013), they appear to adopt similar conceptual definitions: the use of various travel modes in a given time period. In this context, this dissertation measures travel multimodality with a set of indicators, each of which records the frequency of use of a certain mode for a certain trip purpose (Figure 2). Note that this dissertation does not include commitment to or the consequences of certain forms of multimodal travel behaviors such as car ownership, the use of transit pass, and vehicle miles driven (VMD). The inclusion of a wide range of travel-related indicators allows researchers to identify not distinctive travel multimodality but travel-related profiles in a broad sense, which may serve different research goals (K. M. Ralph, 2017).

The critical assumption of the conceptual framework in Figure 2 is that the population consists of several unobserved groups, or latent classes, whose members present distinctive lifestyles or patterns regarding mode choice (i.e., modality styles). Modality styles are *not observed* by researchers, so this dissertation identifies them with the *observed* frequencies of use of travel modes. This dissertation also takes into account trip purposes to see if mode use patterns differ by purpose among the members of the same latent class. This approach is of relevance to millennials' travel multimodality because some studies suggest that these young adults may be more multimodal for one trip purpose but not for the other: e.g., less multimodal for commute trips but more so for non-commute trips (Jaffe, 2013, 2014). With growing popularity of emerging transportation services such as carsharing and ridehailing, but their limited attractiveness for commute trips (e.g., carsharing may not be a cost-effective solution for a one-way commute), this dissertation uses four indicators for commute trips – the frequencies of driving (including carsharing), car as a passenger (including ridehailing), public transit, and active modes – and five indicators for non-commute trips (i.e., leisure trips in this dissertation) – the aforementioned four modes plus the frequency of emerging transportation services (e.g., ridehailing and carsharing) that is counted separately.

In this dissertation, *both* the demographic, economic, and attitudinal characteristics of individuals *and* the built environment attributes account for latent-class membership. While studies in the millennials literature speculate the effects of attitudes on travel behavior, but do not directly measure such effects (Blumenberg et al., 2016; McDonald, 2015), the conceptual framework in Figure 2 (and attitudinal factors in the California Millennials Dataset) allows me to do so. In addition, the separate effects of the built environment on modality styles (thorough the estimation of probabilities, more methodological details in Chapter 4) are measured. Residential self-selection (RSS) is controlled for in the framework (and empirical models in Chapter 6) by the inclusion of attitudes on preferred land-use patterns and desired travel modes (Mokhtarian & Cao, 2008).

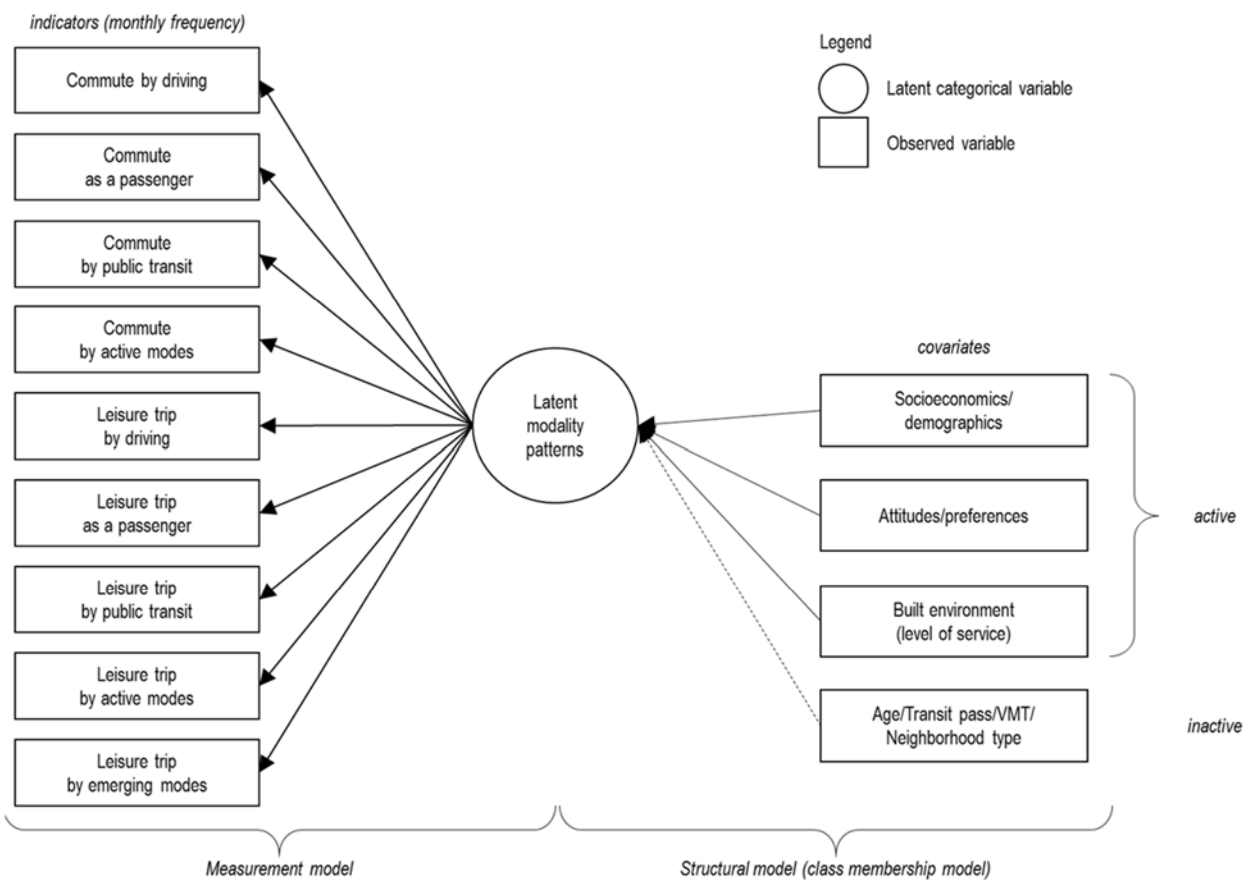


Figure 2 Conceptual Framework of travel multimodality (Fig1 of Molin et al. (2016) is revised)

Note that several individual characteristics are marked as inactive, indicating that these variables do not directly affect latent-class membership. Instead, they help understand the profiles of the members of each latent class in descriptive ways. The framework depicts them as inactive because many of them are either commitment to or the consequences of certain modality styles. For example, vehicle ownership is a separate conscious choice made by individuals, which enables or prevents certain modality styles, and vehicle miles traveled (VMT) is a travel outcome, which is a function of individual characteristics (including attitudes), the built environment attributes, and modality styles. For these reasons, future research can conceptualize them as a part of a comprehensive frame, in which several discrete and continuous variables are jointly modeled: e.g., vehicle ownership, modality styles, and (continuous) the amount of driving.

In Figure 2, *age* is modeled as inactive because this dissertation attempts to understand the effects of *life course events* (through sociodemographic and economic characteristics) and *attitudes* (through factor scores: more details in Chapter 5) on individuals presenting certain modality styles. Note that studies in the millennials literatures employ a binary indicator denoting millennials in their model of travel behaviors, and interpret its statistical significance as the sign of generational differences (Blumenberg et al., 2016; McDonald, 2015). However, it is not clear which types of attitudes the indicator captures: e.g., practical attitudes toward cars, environmental concerns, or proficiency in the use of ICT devices or services. In contrast, this dissertation explicitly examines the effects of various attitudes on modality styles. It also explores the distribution of several modality styles *by age* to see how various attitudes (together with sociodemographic/economic characteristics) account for generational differences in modality styles.

3.1.2 Residential Preferences

With precise home and work/school addresses (geocoded at the Census block group level), this dissertation examines residential preferences of individuals that are *revealed* in actual, constrained choice situations. This examination consists of two parts: the formation of the choice set, which differs by individual, and the investigation of revealed preferences, which refers to the way that individuals derive utility/disutility from the attributes of alternatives in the choice set (Figure 3).

Among many conceptual models in the location choice literature, this dissertation employs a model which assumes that (1) the location of work/school is exogenous to individuals, (2) they form a choice set by applying certain search criteria to available alternatives (i.e., Census block group) surrounding their commute destinations, and (3) they choose an alternative from the choice set, from which they derive the maximum utility (Rashidi, Auld, & Mohammadian, 2012; Rashidi & Mohammadian, 2015). While there are a variety of search criteria that differ by individual, this dissertation focuses on a criterion that many people use, the maximum acceptable commute distance (i.e., search radius) from the commute destination, beyond which individuals do not search for residential neighborhoods any more. This dissertation also assumes that individual or household characteristics account for the search radius that varies from person to person. For example, people living with a school-age child may be willing to live farther away from (i.e., commute longer to) their work/school to find neighborhoods in good school districts.

People earning high incomes may be willing to reduce their commutes (i.e., live closer to their work/school) because of their high value of travel time or they may be willing to accept longer commutes if they desire large houses in suburbs or exurbs. Within the search radius from the commute destination, individuals form a choice set in *manageable* size, or consideration set, and choose an alternative in the set by examining the attributes of the alternatives in the set (e.g., commute distance, affordability, school quality, and density).

This dissertation investigates residential preferences with the assumption that the population consists of several unobserved groups (i.e., latent classes) whose members share similar preferences within the same group, but present heterogeneity across such groups. For example, a group of individuals may prefer neighborhoods in proximity to popular restaurants, cafes, or bars, and another group may tend to choose neighborhoods in well-performing school districts. To identify such latent classes in the sample of individuals, this dissertation adopts a two-stage process: in the membership model, individual/household characteristics account for their class membership; in the choice model, residential preferences are examined for the members of each latent class separately. For example, a single college-educated young adult who just started the first job (i.e., making entry-level incomes) may belong to a latent class whose members present preferences for dense neighborhoods mixed with stores and shops, and a family with school-age children, whose head makes middle-class incomes may be found in another latent class whose members value safe well-maintained neighborhoods in good school districts with neighbors in a similar socioeconomic status. In brief, sociodemographic and economic characteristics with attitudes account for the class membership of individuals, and those in each latent class share unique residential preferences that explain their choice of alternatives in the choice set.

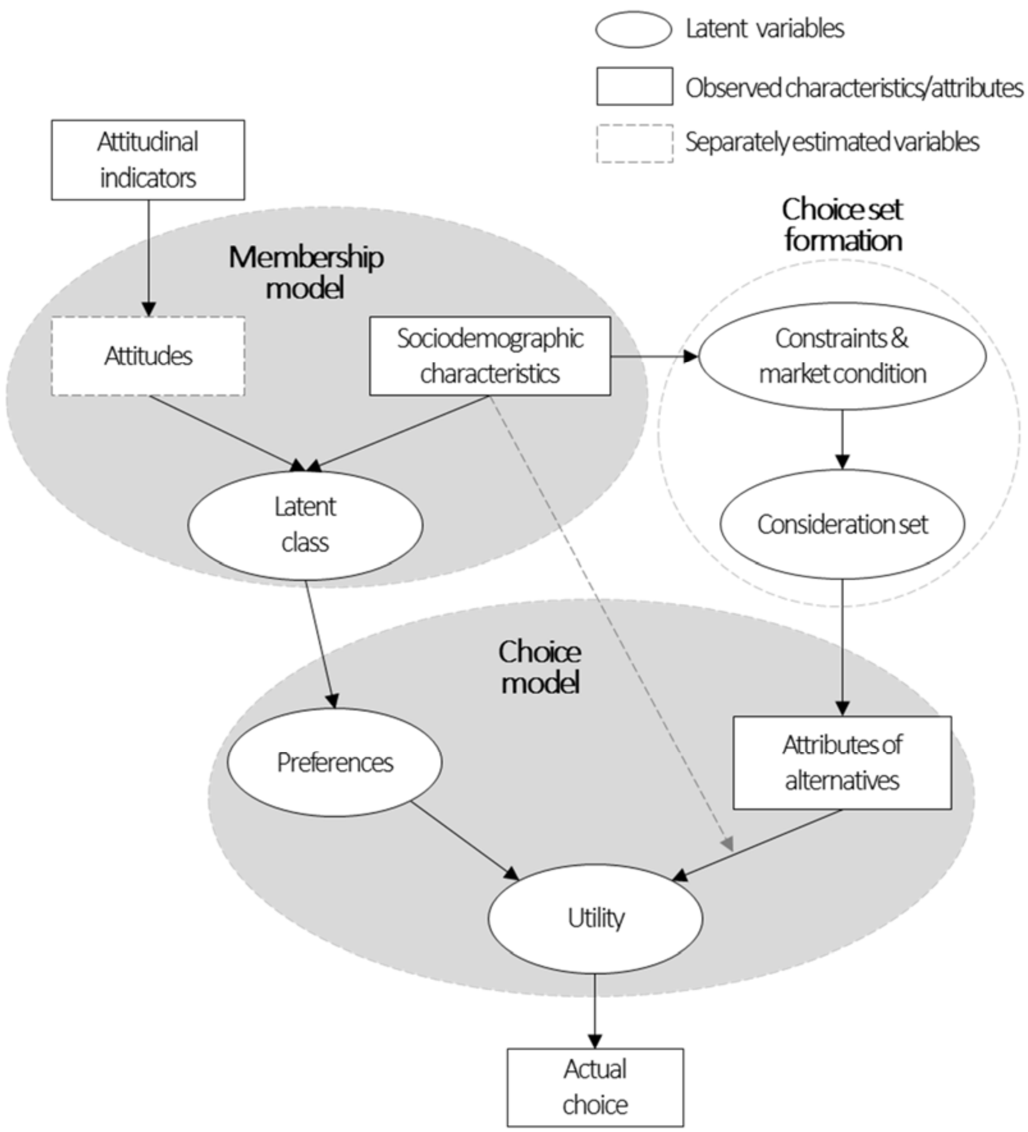


Figure 3 Conceptual Framework of Residential Location Choice

The conceptual framework has several merits. First, it takes into account that the search radius – which affects the formation of the choice set – differs by individual/household characteristics. This approach captures a residential choice situation in more realistic ways than a simpler approach assuming that all individuals use the same maximum acceptable commute distance. Second, the framework allows *both* sociodemographic/economic characteristics and attitudes to affect class membership (which then relates individuals to heterogeneous residential preferences).[1] While many studies and reports claim that millennials may or may not differ in residential choice in part because of attitudes on various dimensions, but their frames (and analytical models) do not include attitudes as the source of heterogeneity (Blumenberg et al., 2015; Coutoure & Handbury, 2017; H. Lee, 2018; Myers, 2016; Raymond & Dill, 2015). Third, the framework illustrates the way in which heterogeneous preferences are revealed in actual, constrained choice situations. For each latent class identified, a separate choice model presents the unique ways that the members of the class respond to the various attributes of alternatives in the choice set: e.g., seek or avoid certain attributes in their neighborhoods.

There are several simplifying assumptions in the framework that researchers may want to remove or replace with less-restricting ones for more realistic residential choice modeling. First, the literature finds that work/school locations are not always exogenous to individuals, but in some cases, the conscious choice made by individuals (Waddell, Bhat, Eluru, Wang, & Pendyala, 2007b). Second, the literatures acknowledges the possibility that attitudes are in part a result of a conscious choice of certain residential neighborhoods (Mokhtarian & Cao, 2008). That is, there may be endogeneity in a conceptual model depicting attitudes *only* as a source of heterogeneity. Third, the framework does not consider a temporary discrepancy between the time of residential relocation and that of a

[1] Note that attitudes are taken from a separate exploratory factor analysis (more details in Chapter 5), instead of being simultaneously estimated in the integration of choice and latent variable model (ICLV) (M. Ben-Akiva et al., 2002).

survey taken by individuals. For example, the *current* sociodemographic, economic, and attitudinal characteristics may not explain the search radius that individuals adopted in the *past*: e.g., when individuals did not have a child or received lower income.

3.2 Methods

This chapter covers three analytical methods used for the analyses of heterogeneous multimodal travel behaviors and residential preferences in the sample of millennials and Gen Xers in California. This dissertation then estimates a latent-class cluster model to identify several forms of modality styles. It estimates a duration model and a latent-class choice model to examine several distinctive residential preferences in Chapter 7.

3.2.1 Latent-Class Cluster Analysis (LCCA)

This dissertation employs latent-class cluster analysis to *probabilistically* assign individuals to traveler groups, each of which is characterized by relatively similar mode use patterns, while maximizing the heterogeneity of these patterns across groups. This analytical approach has several advantages over simpler methods for the identification of multimodal travel behaviors. First, this dissertation attempts to measure multimodality in its entirety, instead of developing a *single* (composite) index. That is, travel multimodality cannot be easily reduced to a mono-dimensional measure such as HHI or Shannon's Entropy (Scheiner et al., 2016). The same values for these indexes may refer to travel behaviors which are very different from each other, and each of which could be the target of unique sets of policies and interventions. Instead, this dissertation classifies individuals into *latent classes* based on multiple indicators, all of which depict the unique mode use patterns of each class.

Second, unlike deterministic classification schemes (Buehler & Hamre, 2014; Diana & Mokhtarian, 2009; Kuhnimhof, Chlond, & von der Ruhren, 2006; Nobis, 2007), latent-class cluster analysis estimates individuals' probabilities of belonging to various latent classes. Each of these classes shows its own profile consisting of average frequencies of use of various modes. Specifically, they are the group-specific probability-weighted averages of indicator variables (the nine mode use frequencies) across the sample. In this context, the latent-class cluster analysis better captures the heterogeneity of multimodal travel behaviors by creating an unobservable construct consisting of multiple modality styles, each of which characterizes a given individual to varying degrees (i.e., with varying probabilities). Third, as for the effects of various factors (i.e., active covariates) on the individuals' probabilities of belonging to various latent classes, the latent-class cluster analysis simultaneously estimates these effects while classifying individuals into various classes. Several researchers, to date, have deterministically identified traveler groups and then assigned individuals to these groups in a separate stage (Buehler & Hamre, 2014; Nobis, 2007; K. M. Ralph, 2017). However, their methods (1) do not guarantee to maximize the heterogeneity between groups, or (2) do not use information available in the active covariates to help estimate the probability of belonging to a given group while simultaneously identifying unobserved groups with heterogeneous behaviors.

The mathematical notation below follows that ofVermunt and Magidson (2016). A latent-class cluster model has a general form specified below.

$$f(\mathbf{y}_i|\mathbf{z}_i^{cov}) = \sum_{x=1}^{K} P(x|\mathbf{z}_i^{cov}) \prod_{t=1}^{T} f(y_{it}|x) \tag{1}$$

$\mathbf{y}_i$ refers to a vector of indicators for case i $(1 \leq i \leq N)$, $\mathbf{z}_i^{cov}$a vector of active covariates for case i that affect $P(x|\mathbf{z}_i^{cov})$, which denotes the probability of individual cases belonging to latent class x $(1 \leq x \leq K)$, and $f(y_{it}|x)$ is the probability density function of t^{th}indicator y_{it} $(1 \leq t \leq T)$ given that case i belongs to class x. Note that the above form assumes that the T indicators are independent given class x, which is called the local independence assumption. Since x is a categorical variable, $P(x|\mathbf{z}_i^{cov})$ has the multinomial logit form.

$$P(x|\mathbf{z}_i^{cov}) = \frac{\exp(\eta_{x|\mathbf{z}_i^{cov}})}{\sum_{x'=1}^{K} \exp(\eta_{x'|\mathbf{z}_i^{cov}})} \tag{2}$$

$$\eta_{x|\mathbf{z}_i^{cov}} = \gamma_{x0} + \sum_{r=1}^{R} \gamma_{xr} z_{ir}^{cov} \tag{3}$$

$\eta_{x|\mathbf{z}_i^{cov}}$ represents the observed part of utility, z_{ir}^{cov} the $r^{th}(1 \leq r \leq R)$ covariate of case i, and γ_{xr} the coefficient estimate of $z_{ir}^{cov}$for latent class x. For identification, $\gamma_{10} = 0$ and $\sum_{x=1}^{K} \gamma_{xr} = 0$ (alternatively, $\gamma_{1r} = 0$ or $\gamma_{Kr} = 0$). Also, the conditional probability of continuous indicator y_{it}, or $f(y_{it}|x)$, is expressed as follows.

$$f(y_{it}|x) = \frac{1}{\sqrt{2\pi\sigma_{t,x}^2}} \exp\{-\frac{1}{2}\frac{(y_{it} - \mu_{t,x})^2}{\sigma_{t,x}^2}\} \tag{4}$$

$\mu_{t,x}$ denotes the mean of t^{th}indicator y_{it} for class x, and $\sigma_{t,x}^2$ the variance of y_{it} class x. To relax the local independence assumption, $\prod_{t=1}^{T} f(y_{it}|x)$ or $f(\mathbf{y}_i|x)$ is jointly modeled as follows.

$$f(\mathbf{y}_i|x) = (2\pi)^{-T/2}|\mathbf{\Sigma}_x|^{-1/2}\exp\{-\frac{1}{2}(\mathbf{y}_i - \boldsymbol{\mu}_x)'\mathbf{\Sigma}_x^{-1}(\mathbf{y}_i - \boldsymbol{\mu}_x)\} \quad (5)$$

$\boldsymbol{\mu}_x$ indicates a mean vector of indicator vector $\mathbf{y}_i$ for class x, and $\mathbf{\Sigma}_x$ the variance and covariance matrix of $\mathbf{y}_i$ for class x. Note that the above structure of $f(\mathbf{y}_i|x)$ allows local dependence patterns to vary from one class to another (i.e., $\mathbf{\Sigma}_x$ differs by class x). In other words, a latent-class cluster model under this general structure estimates $(K-1)\cdot(T + \frac{T(T-1)}{2})$ additional parameters, compared to a simpler model that applies a single variance covariance matrix $\mathbf{\Sigma}$ to all classes. (For this reason, this dissertation employs the simpler model structure.)

In the context of heterogeneous modality styles, the local independence assumption implies that, for a given latent class, its members' frequencies of use of a certain travel mode should not explain, or predict, those for other modes. However, this dissertation finds violations of this assumption: e.g., driving for work/school is statistically correlated with taking public transit for work/school for the same traveler class. Thus, it estimates a latent class cluster model that allows bivariate residual correlations between indicators of different groups of modes for the same trip purposes. Also, in some cases, the model also allows the indicators of the same group of modes for different trip purposes to be correlated (e.g., use of public transit for commute and non-commute trips) (Higgins & Kanaroglou, 2016). M*plus* 7.4 is used for empirical estimation.

3.2.2 Survival Analysis

One essential task for the estimation of residential preferences with discrete choice models is to form the choice set for individuals. If the choice set is not generic (e.g., urban, suburban, and rural), but consists of a large number of unique alternatives (i.e., an unlabeled choice set), researchers need to generate the choice set that consists of the actual choice and unchosen alternatives, which are usually *unobserved*. As for the formation of the choice set, the location choice literature suggests several approaches based on conceptual models for choice processes (Rashidi et al., 2012; Rashidi & Mohammadian, 2015). While random selection among all alternatives leads to consistent parameter estimates for choice models (M. E. Ben-Akiva & Lerman, 1985), the underlying assumption that individuals are aware of all alternatives and make a final decision based on tradeoffs between all alternatives is not realistic. In response, Srinivasan (1987) theorizes that each individual has an "awareness set", which consists of all alternatives known to this individual, an "evoked set", which is a subset of the awareness set and is formed by the application of certain criteria on the awareness set (e.g., maximum acceptable commute distance from work/school), and a "choice set", whose size is more manageable, and which consists of more realistic alternatives.

Among many approaches for the choice set formation, this dissertation employs a duration model, often called a survival/hazard model, by which it estimates one's (natural-log-transformed) commute distance as a function of socioeconomic and demographic characteristics. This dissertation assumes that the 95th percentile estimate is a reasonable proxy for the maximum acceptable commute distance, or the search radius for each individual, within which alternatives are randomly selected. That is, any alternatives beyond the search radius are not attractive or realistic to the individual. Rashidi and his colleagues introduced this approach and demonstrated that it performed better than simple approaches based on random selection (Rashidi et al., 2012). Below, this chapter follows the conventional notation of a survival model to demonstrate the process of the choice set formation for each individual (Cameron & Trivedi, 2005). Researchers often employ survival analysis to model a duration T, a length of time after which the event of interest takes place for the first or next time. In this dissertation, T is a nonnegative continuous random variable representing one's commute distance. Assume that individual i looks for her residential neighborhood and starts to consider each alternative, from those closer to her commute destination to those farther from it. As usual, the cumulative distribution function $F(t)$ and the density function $f(t)$ are:

$$F(t) = \Pr[T \leq t] = \int_0^t f(s)ds \tag{6}$$

Also, the probability of having a commute distance longer than t, or the **survival function**, is:

$$S(t) = \Pr[T > t] = 1 - F(t) \tag{7}$$

Note that $S(0) = 1$ and $S(\infty) = 0$: i.e., this dissertation assumes that the sample does not include those individuals with strong preferences for *always* working at home. In addition, the (baseline) **hazard function** $\lambda(t)$ is the probability of choosing a neighborhood at a certain distance t from the commute destination given that individual i does not choose any neighborhoods whose commute distances are shorter than t.

$$\lambda(t) = \lim_{\Delta t \to 0} \frac{\Pr[t \leq T \leq t + \Delta t \mid T \geq t]}{\Delta t} = \frac{f(t)}{S(t)} \tag{8}$$

Then, by mathematical modification, the survival function is expressed as:

$$S(t) = exp\left(-\int_0^t \lambda(u)du\right) \tag{9}$$

Since this dissertation focuses more on how the hazard function varies by covariates of individuals, $\mathbf{x}_i$ (e.g., sociodemographic/economic characteristics), it estimates the *conditional* hazard function $\lambda(t_i|\mathbf{x}_i)$ by employing a parametric duration model with the **gamma distribution**.

$$\begin{aligned} \lambda(t_i|\mathbf{x}_i) &= \lambda_0\ (e^u) \cdot \exp(\mathbf{x}_i{}'\beta) \\ &= \lambda_0(t_i \exp(-\mathbf{x}_i{}'\beta)) \cdot \exp(\mathbf{x}_i{}'\beta) \end{aligned} \tag{10}$$

, where $\ln t_i$ and the distribution of u are defined as:

$$\ln t_i = \mathbf{x}_i{}'\beta + u_i \tag{11}$$

$$f(u_i) = \exp(\alpha u_i - e^{u_i})\,/\Gamma(\alpha) \tag{12}$$

While some studies have employed parametric duration models with simpler distributions such as the Weibull (Rashidi et al., 2012; Rashidi & Mohammadian, 2015), this dissertation finds that the model with the gamma distribution better fits the data (i.e., AIC and BIC values are lower). For each observation, the contribution to the likelihood is $f(t_i|\mathbf{x}_i)$, for which

$$f(t_i|\mathbf{x}_i) = \lambda(t_i|\mathbf{x}_i) \cdot S(t_i|\mathbf{x}_i) \tag{13}$$

$$\ln L = \sum_{i=1}^{N} \ln[\lambda(t_i|\mathbf{x}_i) \cdot S(t_i|\mathbf{x}_i)] \tag{14}$$

To estimate the search radius, which varies by individual, a survival model is estimated for the commute distance t with $\ln t = \mathbf{x}'\beta + u$ (Equation (11)), in which u follows a gamma distribution whose two parameters are estimated simultaneously with β. Next, the 95$^{\text{th}}$ percentile of u (based on the estimated parameters of its distribution) is taken, $\mathbf{x}'\beta$ is added to it, and then, the result is exponentiated (for the reversal of the log-transform). For the small number of cases (5% of our sample) whose actual commute distances are longer than their 95$^{\text{th}}$ percentile estimates, I use their actual commute distances plus 0.1 mile as their search radius. The survival model includes socioeconomic and demographic characteristics as explanatory variables and the network-derived commute distance as its dependent variable. SAS 9.4 is employed for the estimation of the commute distance.

3.2.3 Latent-Class Choice Model (LCCM)

I employ a latent-class choice model (LCCM) to uncover unobserved groups in the sample, whose members show residential preferences that are similar within each group but heterogeneous across groups. LCCM simultaneously estimates the probabilities of individuals belonging to various unobserved groups, or latent classes, and the probability of choosing each alternative in the choice set conditional on belonging to a certain latent class. The latter sub-model is called a *choice model*, and the former a *membership model*. Below, this chapter explains how the two models are estimated by borrowing equations from a previous study and modifying their notation (Greene & Hensher, 2003). To predict individuals' choice of residential location with a conditional logit model, the probability of individual i choosing alternative j given this individual belongs to latent class q is

$$\mathrm{Prob}[choice\ j\ by\ individual\ i\ |class\ q] = \frac{\exp(\mathbf{x}_{ij}'\boldsymbol{\beta}_q)}{\sum_{j=1}^{J_i}\exp(\mathbf{x}_{ij}'\boldsymbol{\beta}_q)} = P_{i|q}(j)\,. \qquad (15)$$

Here, J_i refers to the size of the choice set for individual i, $\mathbf{x}_{ij}$ a set of attributes for alternative j of individual i, and $\boldsymbol{\beta}_q$ is the vector of coefficients of these attributes for individuals belonging to class q. To simplify, I use $P_{i|q}$ instead of $P_{i|q}(j)$. Since the class assignment of individuals is not known to researchers, it needs be estimated. Below is the membership model of the LCCM. Here, H_{iq} is the *prior* probability of individual i belonging to q. With a multinomial logit model, this probability is expressed as

$$H_{iq} = \frac{\exp(\mathbf{z}_i'\boldsymbol{\theta}_q)}{\sum_{q=1}^{Q}\exp(\mathbf{z}_i'\boldsymbol{\theta}_q)}\,. \qquad (16)$$

Here, Q refers to the number of latent classes in a sample, $\mathbf{z}_i$ is a set of individual-specific attributes that affect the probabilities of belonging to various latent classes, and $\boldsymbol{\theta}_q$ is the coefficients of these attributes for those who belong to class q. (Note that for normalization, one of the $\boldsymbol{\theta}_q$'s needs to be set to zero: e.g., $\boldsymbol{\theta}_Q = \mathbf{0}$.) Thus, the unconditional probability of individual i choosing alternative j is

$$P_i = \sum_{q=1}^{Q} H_{iq} P_{i|q} \,. \tag{17}$$

Then, the log likelihood for an entire sample of size N is

$$\ln L = \sum_{i=1}^{N} \ln P_i = \sum_{i=1}^{N} \ln \left[\sum_{q=1}^{Q} H_{iq} P_{i|q} \right]. \tag{18}$$

Using the Bayes theorem, a *posterior* probability is computed as follows.

$$\widehat{H}_{q|i} = \frac{\widehat{P}_{i|q} \widehat{H}_{iq}}{\sum_{q=1}^{Q} \widehat{P}_{i|q} \widehat{H}_{iq}} \,. \tag{19}$$

While studies suggest that, among various $\widehat{H}_{q|i}$ (q = 1, 2, …, Q), individual i is assumed to belong to the class with the highest $\widehat{H}_{q|i}$, this dissertation uses the probabilities of individuals, not their assignment to one class or another, to compute the shares of latent classes by age and geography at an aggregate level. As for the estimation steps with the Expectation Maximization (EM) algorithm, refer to previous studies (Greene, 2001; Greene & Hensher, 2003).

As for the LCCM estimation, two issues need be solved. First, researchers do not know a priori the *right* number of latent classes, Q, so they need to run models with varying Q and choose the most appropriate solution. Studies suggest using information-based criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion

(BIC) to find the best solution. Here, this dissertation also considers the interpretability of various results: e.g., whether the choice model produces coefficient estimates for each latent class, which are consistent with the findings of the location choice literature. Latent GOLD 5.1 is employed for estimation. Second, it is not clear which variables need be included in the choice model or the membership model. With the help from the location choice literature (Figure 2 of Chapter 3), an LCCM is estimated in Chapter 7, in which the socioeconomic status and attitudes of individuals enter the membership model, objective alternative-varying attributes enter the choice model, and the interaction terms between individual-level socioeconomics and alternative-level attributes are added to the choice model.

3.3 Data

3.3.1 California Millennials' Dataset

This dissertation employs the California Millennials' Dataset (henceforth, "the Dataset"), which is built from an online transportation survey conducted in California in fall 2015. The goal of the survey was to collect *rich* information that would help examine the complex relationships surrounding the travel behaviors and mobility/location choices of millennials and members of Generation X (i.e., Gen Xers). Thus, the survey collected a wide range of information from individuals under the following eleven sections.

1. Individual attitudes and preferences
2. Use of online social media and adoption of technology
3. Residential location and living arrangements
4. Employment and work/study activities
5. Transportation mode perceptions
6. Current travel choices
7. Awareness, adoption, and frequency of use of emerging transportation services
8. Driver's license and vehicle ownership
9. Previous travel behavior and residential location
10. Expectations for future events
11. Sociodemographic traits

The Dataset includes 1,975 cases of millennials and Gen Xers. These individuals were recruited via an opinion panel: They voluntarily registered themselves in the panel and participated in various online surveys. The research team that built the Dataset (it includes the author of this dissertation, and henceforth “the team”) adopted a quota sampling approach to collect sufficient cases across six regions of California and three neighborhood types (urban, suburban, and rural). (Figure 4). Then, the team computed weights at the individual level so that weighted analyses of the Dataset could represent the behaviors and choices of the two generations in California. For doing so, the team applied a combination of cell weights and the iterative proportional fitting (IPF) algorithm. In the weighting process, the team used targets for gender, race and ethnicity, student/worker status, presence of children in the household, and household income from the 2015 US Census American Community Survey 5-year estimate. This dissertation reports weighted analyses. Initially, the team envisioned creating a rotating panel for the analysis to tackle longitudinal change in behaviors and choices of the same individuals in response to life course events. In this sense, the Dataset is the first wave of the panel, and its second wave is being administered in summer 2018. For more information on survey design, administration, data cleaning and enriching, and descriptive analyses, refer to the project reports (Circella, Alemi, Tiedeman, et al., 2017; G. Circella, F. Alemi, K. Tiedeman, S. Handy, & P. L. Mokhtarian, 2018b; Circella et al., 2016).

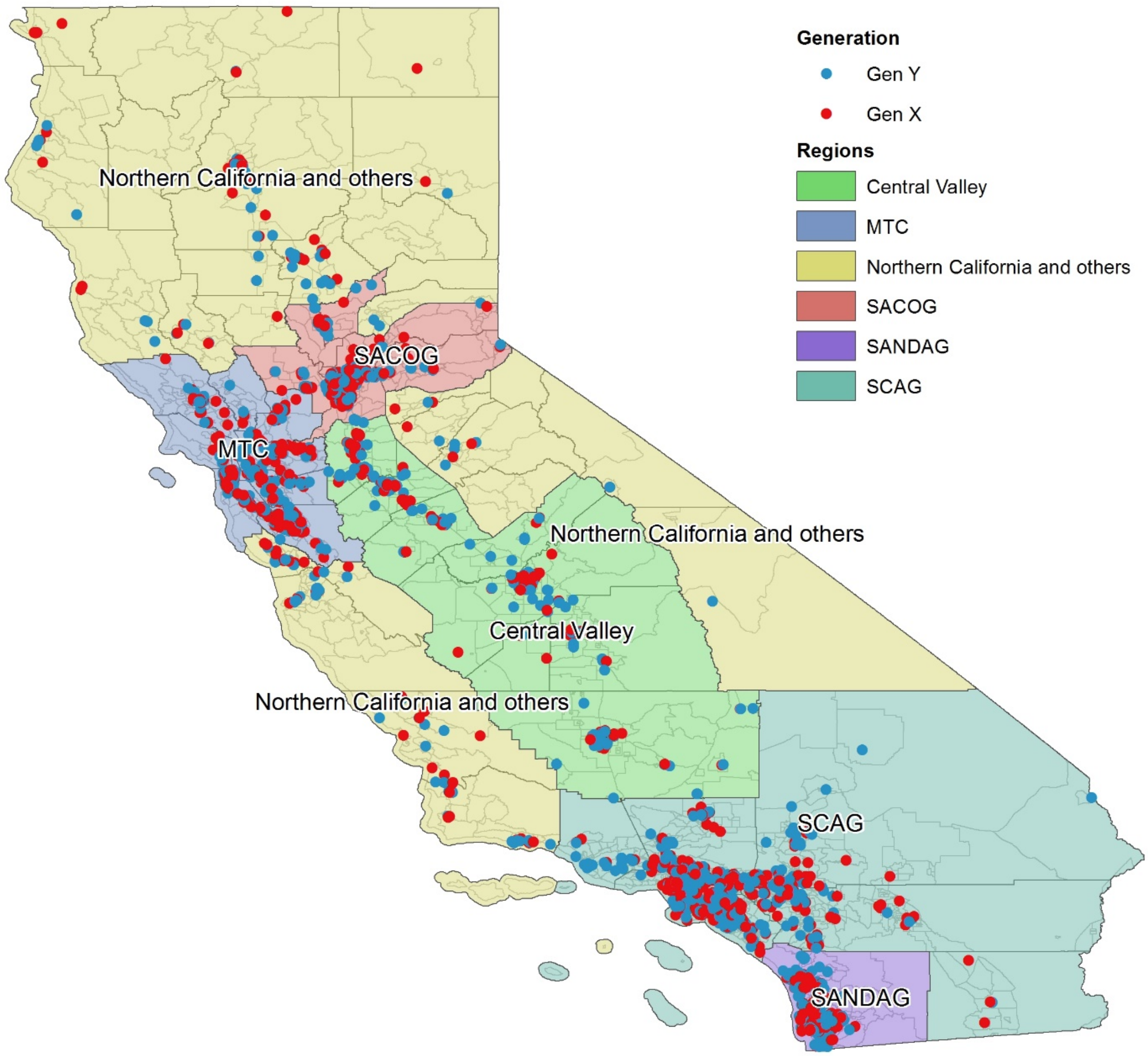


Figure 4 Distribution of millennials and Gen Xers in the dataset, based on their geocoded residential addresses (Circella, Alemi, Tiedeman, et al., 2017)

3.3.2 Attitudinal Factors

For attitudes and preferences, the Dataset contains individuals' level of agreement with 66 statements on a 5-point Likert-scale from "Strongly disagree" to "Strongly agree". The team conducted a factor analysis and identified 17 factors as the best solution, leaving 14 stand-alone statements that were not included in the final factor solution (but were retained for further analysis), based on multiple criteria including interpretability. Table 1 presents the 17 factors and 52 statements that loaded on these factors. For each factor, only those statements with loadings greater than 0.3 or smaller than -0.3 are listed here.

Table 1 Final results of the factor analysis (Circella, Alemi, Tiedeman, et al., 2017)

Factors and Loaded statements	Factor Loading
Pro-store shopping	
I prefer to shop in a store rather than online.	0.998
I enjoy shopping online.	-0.413
Pro-environmental policies	
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.937
We should raise the price of gasoline to provide funding for better public transportation.	0.841
The government should put restrictions on car travel in order to reduce congestion.	0.331
Variety Seeking	
I like trying things that are new and different.	0.592
I have a strong interest in traveling to other countries.	0.405
Pro-exercise	
The importance of exercise is overrated.	-0.822
Getting regular exercise is very important to me.	0.587
Pleasant commute	
My commute is stressful.	-0.802
My commute is generally pleasant.	0.689
Traffic congestion is a major problem for me personally.	-0.544
The time I spend commuting is generally wasted time.	-0.501
Getting stuck in traffic does not bother me that much.	0.305
Pro-suburban	
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go to.	0.764
I prefer to live close to transit even if it means I will have a smaller home and live in a more crowded area.	-0.69
I like the idea of living somewhere with large yards and lots of space between homes.	0.428
I like the idea of having different types of businesses (such as stores, offices, restaurants, banks, and library) mixed in with the homes in my neighborhood.	-0.357
Responsive to environmental effect and price of travel	
The environmental impacts of the various means of transportation affect the choices I make.	0.739
I am committed to using a less polluting means of transportation as much as possible.	0.598
The price of fuel affects the choices I make about my daily travel.	0.532
To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle.	0.384
Established in Life	
I’m already well-established in my field of work.	0.704
I’m still trying to figure out my career (e.g. what I want to do, where I’ll end up).	-0.636
I am generally satisfied with my life.	0.387
Long term suburbanite	
I picture myself living long-term in a suburban setting.	0.819
A house in the suburbs is the best place for kids to grow up.	0.568

Table 1 continued

Factors and Loaded statements	Factor Loading
I picture myself living long-term in an urban setting.	-0.310
Must own car	
I definitely want to own a car.	0.697
I am fine with not owning a car, as long as I can use or rent one any time I need it.	-0.500
Car as a tool	
The functionality of a car is more important to me than its brand.	0.579
To me, a car is just a way to get from place to place.	0.480
Climate change concerned	
Greenhouse gases from human activities are creating major problems.	0.796
Any climate change that may be occurring is part of a natural cycle.	-0.656
It is pointless for me to try too hard to be more environmentally friendly because I am just one person.	-0.307
Technology embracing	
Having Wi-Fi and/or 3G/4G connectivity everywhere I go is essential to me.	0.609
Getting around is easier than ever with my smartphone.	0.492
Learning how to use new technologies is often frustrating.	-0.359
Technology creates at least as many problems as it does solutions.	-0.310
Monochronic (Pro-monotasking)	
It's best to finish one project before starting another.	0.518
I like to juggle two or more activities at the same time.	-0.346
Time/mode constrained	
My schedule makes it hard or impossible for me to use public transportation.	0.580
I am too busy to do many things I'd like to do.	0.443
Most of the time, I have no reasonable alternative to driving.	0.388
Pro-social	
Social media (e.g. Facebook) makes my life more interesting.	0.505
People are generally trustworthy.	0.442
I enjoy the social aspects of shopping in stores.	0.323
Materialism	
I would/do enjoy having a lot of luxury things.	0.441
I prefer to minimize the material goods I possess.	-0.412
For me, a lot of the fun of having something nice is showing It off.	0.387
I like to be among the first people to have the latest technology.	0.380
To me, owning a car is a symbol of success.	0.316

3.3.3 Land-Use Attributes

For built environment attributes, the team appended data from external sources based on the home and work/school addresses reported by individuals. The team first geocoded their addresses (i.e., converted each address to its geographic coordinates, or a pair of a latitude and a longitude) by employing the Google Maps Application Programming Interface (API). Next, with these geocodes, the team matched each case with attributes on land use and transportation systems from several sources. The Smart Location Database (SLD) of the US Environmental Protection Agency (USEPA) provides a wide range of land use variables under 5D's (Ewing & Cervero, 2010; Ramsey & Bell, 2014), which the team factor-analyzed to obtain composite indexes capturing *activity intensity* and *land-use balance*. For the level of service by public transit, the team collected the *transit connectivity index*, i.e. a composite index that takes into account bus routes and train stations within walking distance for each census block group, from alltransit.cnt.org (CNT, 2016). This dissertation employs these three variables for the analysis of travel multimodality.

For the analysis of residential preferences, this dissertation further developed a rich set of land-use attributes and sociodemographic characteristics at the 2010 US Census block group level. The land-use metrics under 5D's come from the USEPA SLD; the counts of various types of businesses/places from the Google Places API; and the level-of-service attributes for walking, biking, and public transit from an online open-source database, walkscore.com for the 22,130 block groups in California. With the variables from these sources, three underlying factors are extracted: *Amenities*, *Land-use mix*, and *Density* (Table 2). In addition, the shares of racial groups, median household income, median home value, and media rent of individual block groups come from the 2015 American Community Survey 5-year estimates, and a composite measure for the quality of elementary schools comes from an online open-source database, greatschools.org.

In this dissertation, the neighborhood classification scheme of Salon (2015) is also used as an inactive covariate. Her scheme is based on land-use attributes at the census tract level in California. Her original naming for five neighborhood types are *central city*, *urban*, *suburban*, *rural in urban*, and *rural*, and in this dissertation, the fourth type is renamed as *exurban*, which better captures the nature of its land-use patterns and geographical locations.

Table 2 Factor Analysis on the Built Environment Attributes (n=22,130 block groups in California)

Variable	Source	Amenities	Land-use mix	Density
ln(# of bars+1)	Google Places API	0.868		
ln(# of cafes+1)	Google Places API	0.847		
ln(# of clothing stores +1)	Google Places API	0.792		
ln(# of art museums +1)	Google Places API	0.773		
ln(# of clubs +1)	Google Places API	0.755		
ln(# of gyms +1)	Google Places API	0.737		
ln(# of spas +1)	Google Places API	0.728		
ln(# of restaurants +1)	Google Places API	0.706		0.304
ln(# of shoe stores +1)	Google Places API	0.679		
ln(# of museums +1)	Google Places API	0.619		
ln(# of convenience stores +1)	Google Places API	0.540		
ln(# of malls +1)	Google Places API	0.530		
transit score	walkscore.com	0.519		
bike score	walkscore.com	0.435		
ln(# of department stores +1)	Google Places API	0.409		
Employment and household entropy	US EPA Smart Location Database		0.977	
ln(job per household)	US EPA Smart Location Database		0.854	
Employment and household entropy, based on trip productions and attractions	US EPA Smart Location Database		0.772	
ln(worker per employment)	US EPA Smart Location Database		-0.740	
Household workers per job equilibrium index	US EPA Smart Location Database		0.713	
Trip productions and attractions equilibrium index	US EPA Smart Location Database		0.697	
5-tier employment entropy[1)]	US EPA Smart Location Database		0.620	
ln(street density)	US EPA Smart Location Database			0.907
ln(intersection density excluding auto-oriented)	US EPA Smart Location Database			0.893
ln(population density)	US EPA Smart Location Database			0.891

ln(street density of pedestrian-oriented links)	US EPA Smart Location Database			0.878
ln(land area in the block group)	2010 US Census TIGER shapefile			-0.867
ln(total area in the block group)	2010 US Census TIGER shapefile			-0.863

Table 2 continued

Variable	Source	Amenities	Land-use mix	Density
ln(housing density)	US EPA Smart Location Database			0.846
ln(activity density)	US EPA Smart Location Database			0.798
ln(# of jobs in 45 minutes by driving)	US EPA Smart Location Database			0.571
ln(intersection density of pedestrian-oriented with three legs)	US EPA Smart Location Database			0.375
ln(intersection density of pedestrian-oriented with four or more legs)	US EPA Smart Location Database			0.305

* Loadings between -0.3 and +0.3 are now shown. Rotation method: Oblimin with Kaiser Normalization
1) Five tiers of jobs: Retail (CNS07 in 2010 LEHD), Office (CNS09, CNS10, CNS11, CNS13, and CNS20), Industrial (CNS01, CNS02, CNS03, CNS04, CNS05, CNS06, and CNS08), Service (CNS12, CNS14, CNS15, CNS16, and CNS19), and Entertainment (CNS17 and CNS18)

3.3.4 Sample Distribution of Key Variables

This section explores the difference between millennials and Gen Xers in terms of key variables in the California Millennials' Dataset (N=1,975). Note that in this dissertation, millennials refer to those who were 18 to 34 years old in 2015, or born from 1981 to 1997. Table 3 presents that on average, fewer millennials live with the partner or a child, but more of them live with parents than Gen Xers. Table 4 shows that on average, more millennials study full-time or part-time, and fewer millennials work full-time compared to Gen Xers in the Data (more millennials work part-time). Interestingly, on average, fewer millennials earn a college or graduate degree than Gen Xers, which appears at odds with aggregate-level statistics in government documents and reports (Fry et al., 2018; Taylor, Fry, & Oates, 2014). Note that, Table 4 compares millennials from 18 to 34 with Gen Xers from 35 to 50: i.e., some Gen Xers in the Data may have not yet earned such degrees when they were between 18 and 34. Or, Gen Xers in the Data, who belong to an *online* opinion panel, may be more educated than a typical Gen Xer in the population. Table 5 displays that on average, more millennials rent homes or are provided residence by others (e.g., relatives or employers) than Gen Xers. Table 5 also presents that on average, millennials make a larger proportion among those in the lower income bracket than Gen Xers in the California Millennials' Dataset. Millennials earn less in part because they have started their career recently or some of them have not yet establish an independent household that has two workers and make higher incomes.

Table 3 Living Arrangements by Generation (weighted)

Table 4 Study/Work Status and Educational Attainment by Generation (weighted)

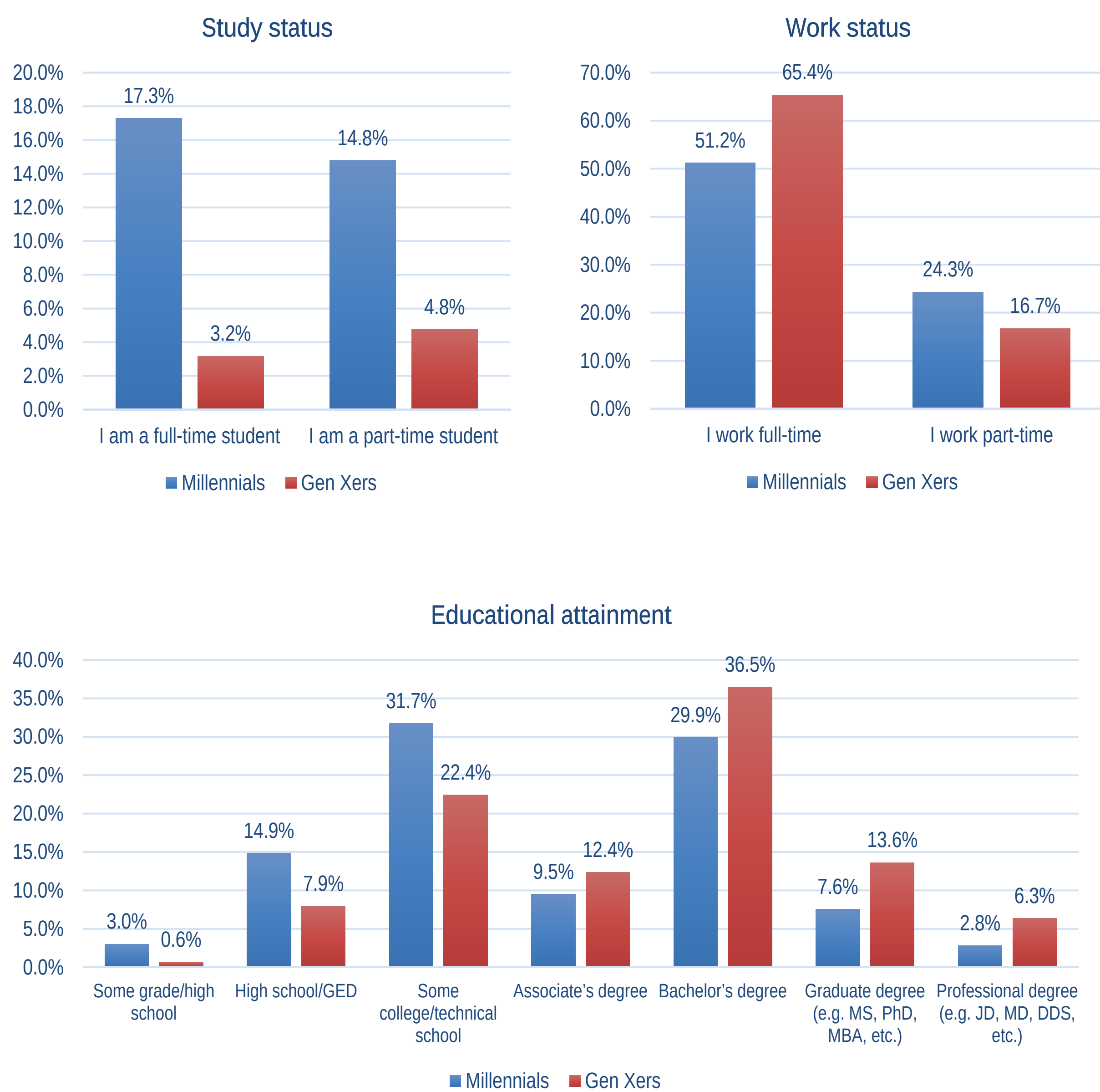
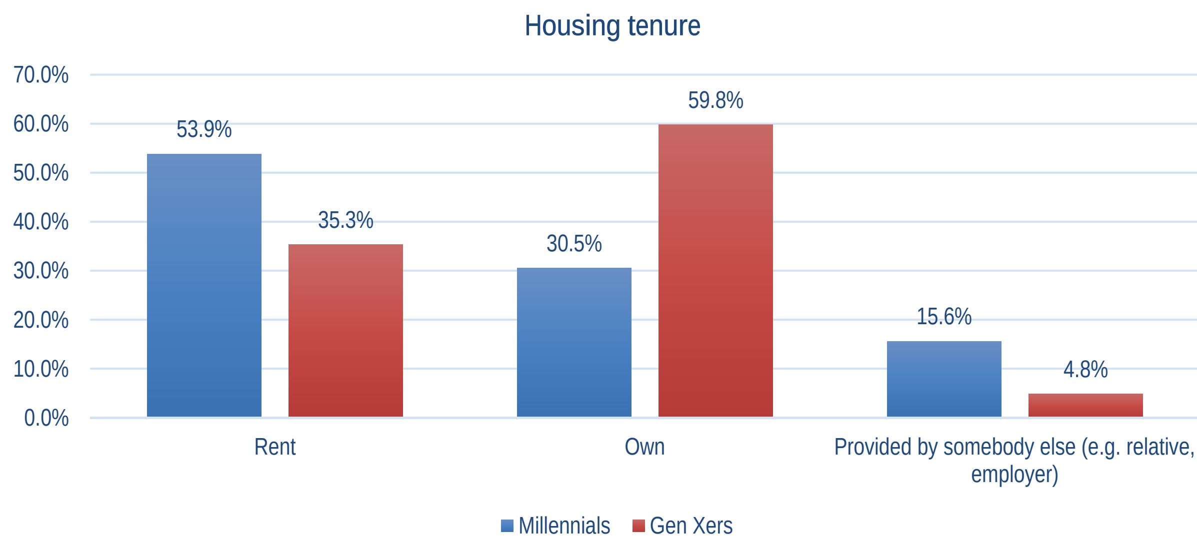
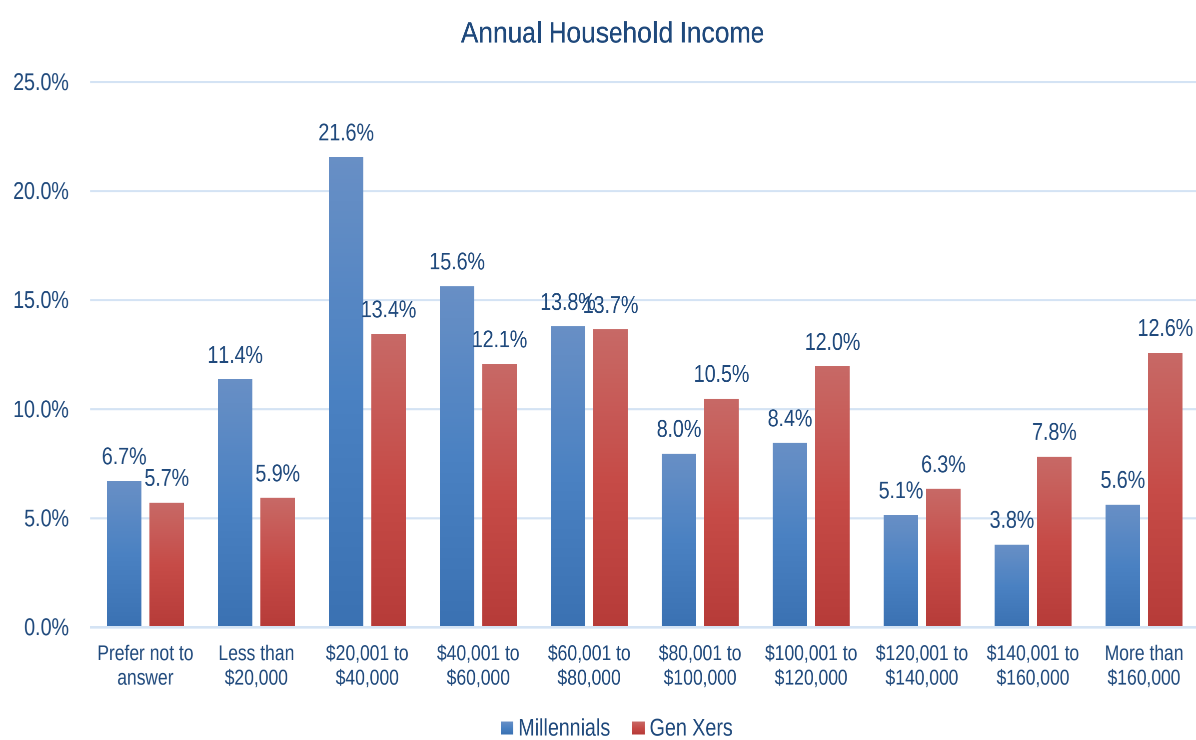


Table 5 Housing Tenure and Annual Household Income by Generation (weighted)

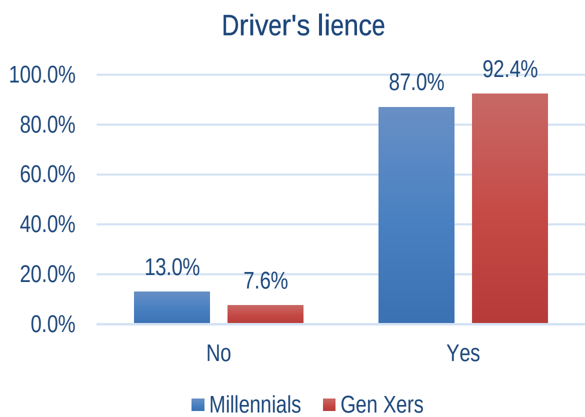


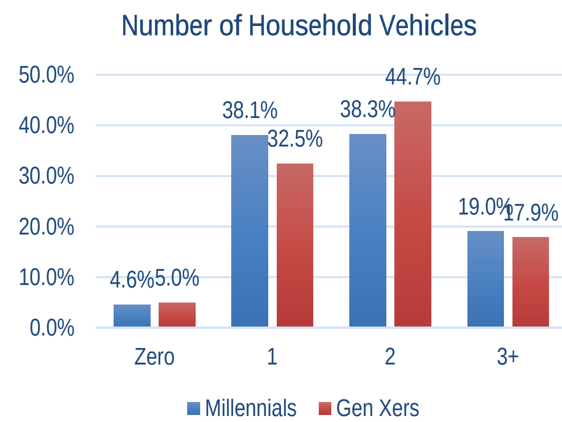


As for mobility-related choices, Table 6 show that on average, fewer millennials in the California Millennials' Dataset obtain a driver's license than Gen Xers. Many millennials live in households with one vehicle, while many Gen Xers live in households with two vehicles in part because more Gen Xers form households with the spouse and a child and have complex travel demands. As for the availability of household vehicles, more Gen Xers report 100% of the times (when they need), while fewer millennials do so. This difference appears to account for their use of vehicles and other transportation modes, which will be further examined in the next chapter.

While reports, media, and studies suggest that millennials present different attitudes and perceptions than older cohorts, millennials in the California Millennials' Dataset do not show substantial differences in key attitudinal factors compared to Gen Xers. Several patterns in Table 7 are worth mentioning. While millennials also place non-use values on cars, they do not think cars as a necessity as much as Gen Xers. In general, perceptions of three transportation modes, personal vehicles, public transit, and active modes, do not differ much by generation. Still, the California Millennials' Dataset presents *local* differences by generation, especially in responses for the "Very good" category. More Gen Xers perceive personal vehicles as very good, and more millennials accept public transit or active modes as very good modes for them. On average, fewer millennials prefer suburban lifestyles, and more of them are familiar with and frequent users of ICT devices and services. Surprisingly, millennials purse materialistic lifestyles slightly more than Gen Xers. Given that they do not necessarily prefer to own cars, their material lifestyles may take different forms from those of Gen Xers: e.g., the purchase of latest tech devices.

Table 6 Driver's License and Car Availability by Generation (weighted)





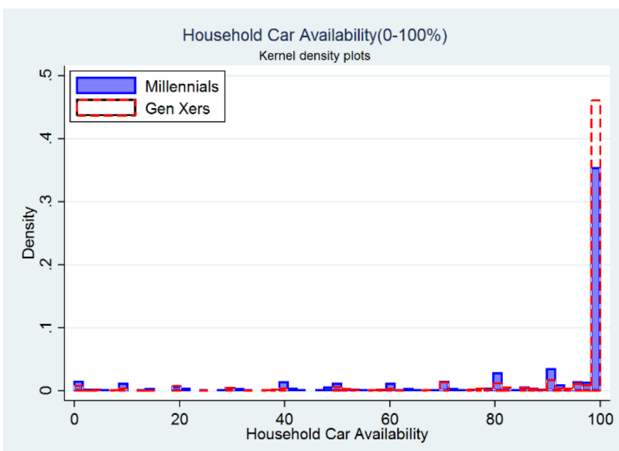
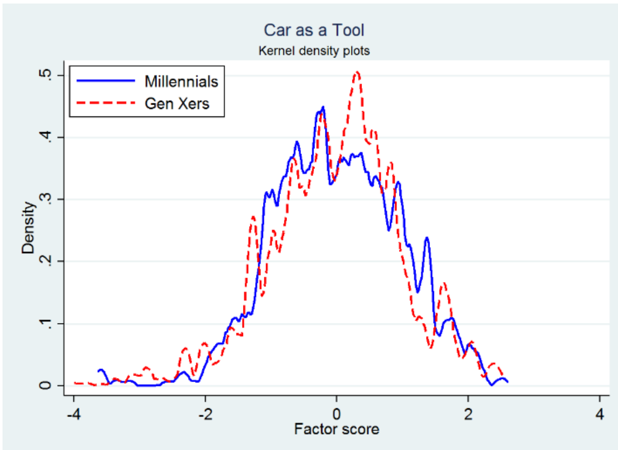
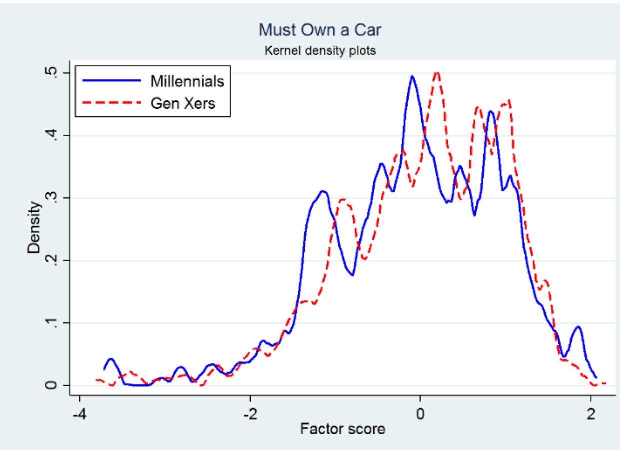
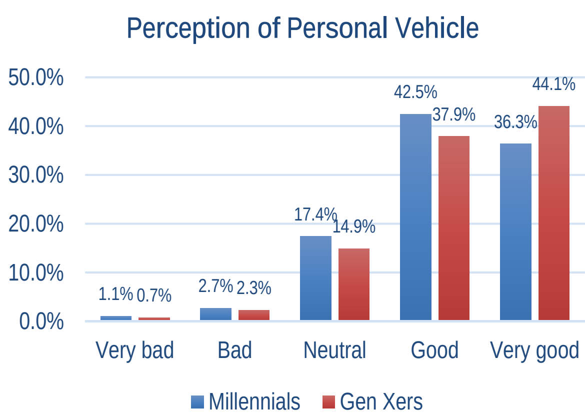
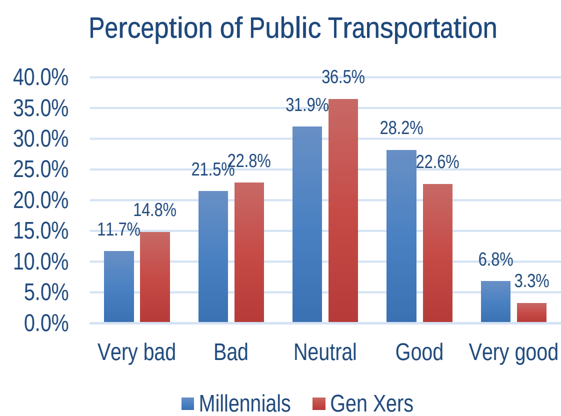


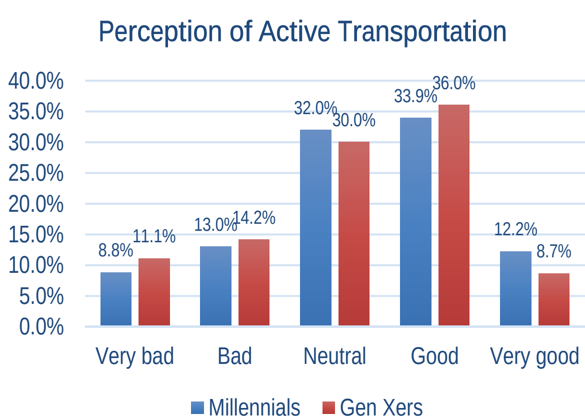
Table 7 Attitudes and Perceptions by Generation (weighted; factor scores are standardized)

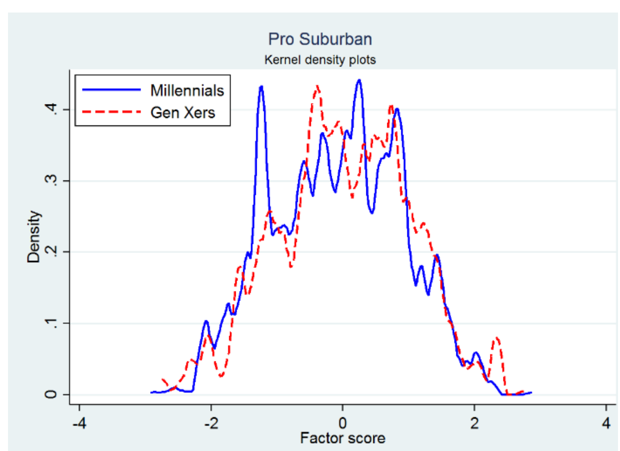












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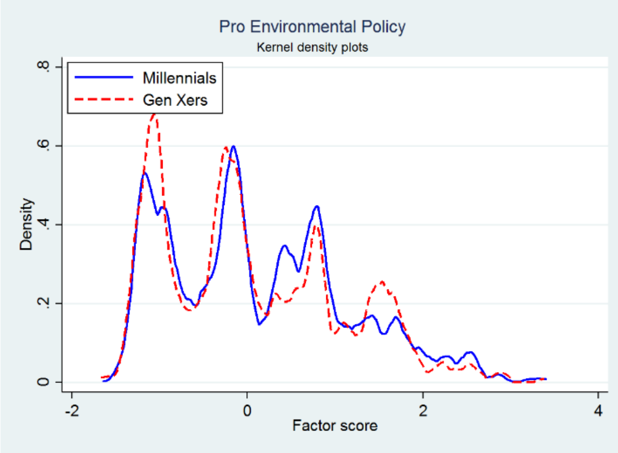
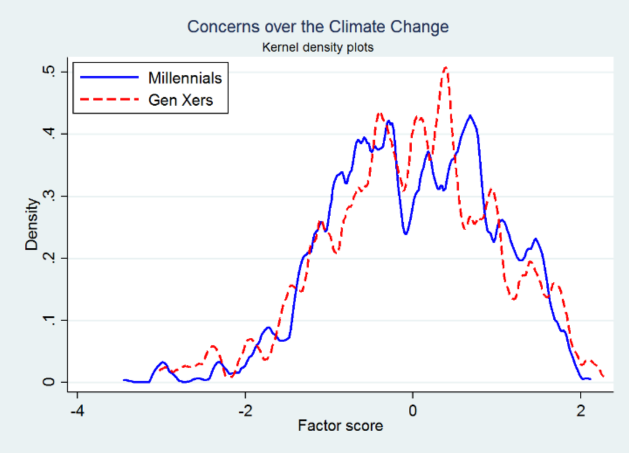
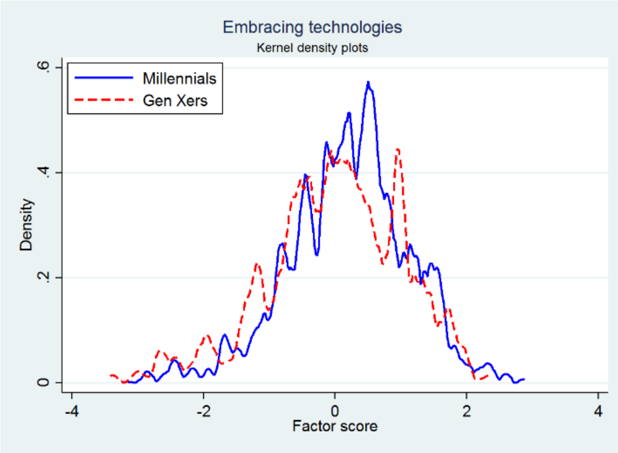
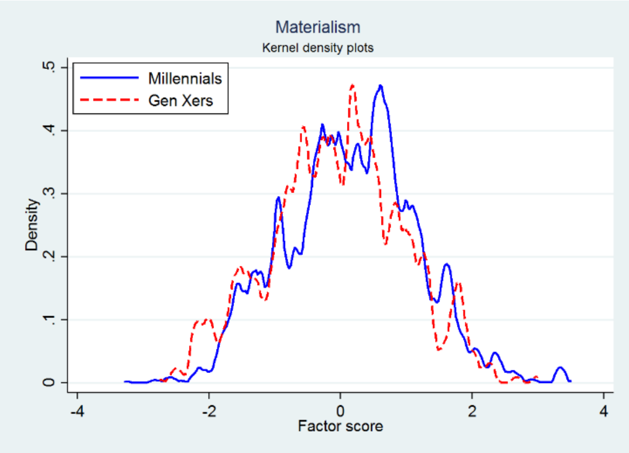
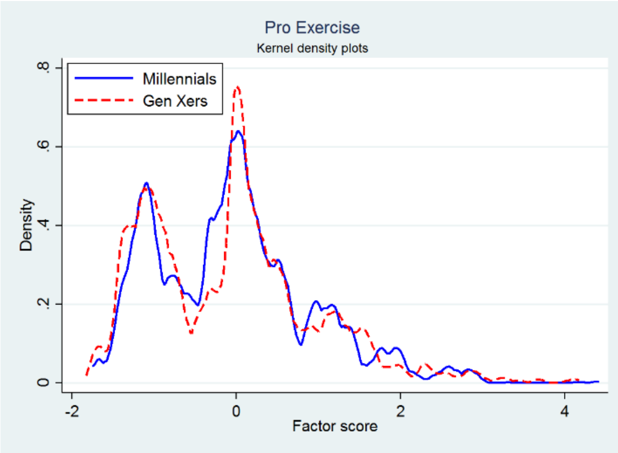
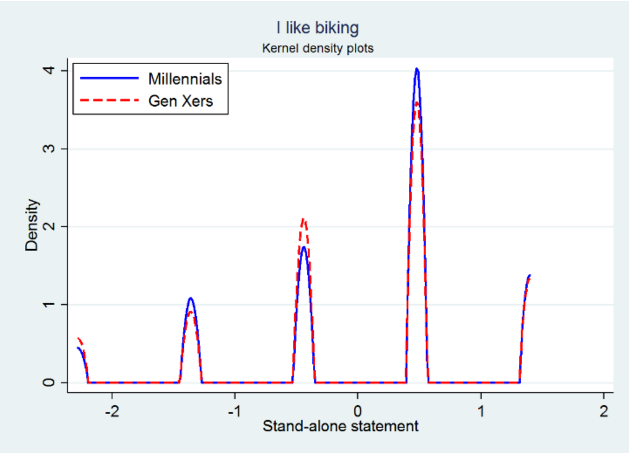












3.3.5 Limitations of the California Millennials' Dataset

The California Millennials' Dataset contains more information under a wider range of categories compared to conventional transportation surveys, which many studies employed to examine generational differences in travel behavior and location choice. Still, the dataset has several limitations. First, the individuals in the Dataset were recruited from a commercial opinion panel, whose members may differ from random individuals in the population. The team minimized any systematic biases by applying weights based on sociodemographic and economic characteristics. Still, there may be systematic differences between the opinion panel and the general public in terms of unobserved characteristics. Second, some questions in the survey were asked for accuracy at the expense of precision: e.g., as for mode choice, the survey asked the frequency of use of various modes with seven categorical options, not counts per week or month. Given the variety of topics in the survey and its length, the team made such inevitable decisions in the survey design process: otherwise, the respondents would have felt a heavier response burden. For future survey design and data collection, the combination (i.e., coordinated administration) of an in-depth survey (e.g., the California Millennials' Dataset) and a typical trip diary (e.g., National Household Travel Survey) for the same individuals would collect *both* rich and precise information.

Third, not all variables that the literature shows to be relevant for travel behavior and location choice of millennials were asked in the survey to reduce the response burden of the already lengthy survey. For example, millennials now undergo their 20s and early 30s, during which many people change beliefs, values, perceptions, lifestyles, and self-identity in part in response to various life course events. However, the survey could not ask all possible events: the age at which individuals started their first job was not included in the survey. The survey did ask about key life course events in the last three years including starting a new job, but not outside of this time window. Moreover, the California Millennials' Dataset does not include attitudes and preferences of the other household members of the respondents. These variables may not matter much in the analysis of travel behaviors, but may be critical in the analysis of location choice. After all, residential choice is a group decision made by a household, whose members often present preferences for various neighborhood attributes in opposite directions. Another critical information is about financial situation in detail: e.g., the amount of the debt balance from student loans or monthly payment, which may affect residential location via housing tenure choice.

CHAPTER 4. ARE MILLENNIALS MORE MULTIMODAL? A LATENT-CLASS CLUSTER ANALYSIS WITH ATTITUDES AND PREFERENCES

4.1 Introduction

A few studies have analyzed millennials' multimodality. According to these studies, millennials represent several distinctive traveler groups based on daily travel patterns and longer-term mobility choices. By analyzing the 2009 National Household Travel Survey (NHTS), K. M. Ralph (2017) suggested that four groups of travelers could be identified: *drivers*, *long-distance trekkers*, *multimodals*, and *carless.* Among these groups, multimodals made more than half of their trips by walking, biking, and public transit; were less likely to have a driver's license and access to household vehicles; but traveled more frequently than the first two groups who traveled almost exclusively in automobiles. Unlike the popular depiction in the mass media, only 3.6% of those aged between 16 and 36 fit into this category in the 2009 NHTS. With a simpler measure of travel multimodality, Buehler and Hamre (2014) found that younger people tended to travel more by walking, biking, and using public transit than their older counterparts. The authors also showed that the longer the measurement period, the higher the proportion of users that would be categorized as multimodal travelers in the population. For example, while only 22.1% of respondents in the 2009 NHTS data used more than one mode on the surveyed day, the share of "multimodal travelers" increased to 72% if its definition includes users that adopted different modes on different days of the same week. Thus, identifying multimodal travelers based only on daily travel patterns may omit a substantial portion of the population, who may be (nearly) as responsive to policies and interventions as daily multimodals (Buehler & Hamre, 2014; Molin et al., 2016; Van Exel & Rietveld, 2009). While the aforementioned studies analyzed one or more cross-sectional datasets separately, Vij and his colleagues (Vij, Gorripaty, & Walker, 2017) estimated *pooled* models using two repeated cross-sectional datasets to see if (in the aggregate) young and older adults prefer multimodality more over time. Using two regional travel survey datasets in the San Francisco Bay Area in 2000 and 2012, they reported that “Car Preferring Multimodals” increased their shares in the population while “Complete Car Dependents” decreased in the 2000s. Interestingly, in their study, the trend of increasing multimodals was not limited to young adults, but present in all age groups.

Researchers have developed a variety of multimodality definitions and indices, most of which have not been applied to studies with a focus on millennials. Buehler and Hamre (2014) classified all individuals into three traveler groups: (a) those who use only automobiles, (b) those who use both automobiles and several alternatives (walking, biking, and public transit), and (c) those who use only these non-automobile modes. Although intuitive and convenient, this approach fails to capture the continuous degree of mono/multimodality that each traveler might have and its multidimensionality. Scheiner et al. (2016) tested several continuous measures, each of which focused on specific aspects of multimodality. For example, the share of trips made with the most frequently used mode captures individuals’ degree of concentration on a single mode, but does not take into account the distribution of use across other modes. In contrast, the *Herfindahl-Hirschman Index (HHI)* and *Shannon’s Entropy* index measure how concentrated or dispersed individuals’ use patterns are across multiple modes, but do not consider what their primary mode is. Other researchers attempted to measure the multidimensional nature of multimodality. Diana and Mokhtarian (2009) classified survey respondents from France and the US into four traveler types using a k-means cluster analysis on objective, subjective, and desired levels of travel by various modes. K. M. Ralph (2017) employed a latent profile analysis in which she included seven indicators of mobility choices for various time horizons, from daily travel patterns to medium-term commitments such as driver's license, car ownership, and annual miles driven. Molin et al. (2016) avoided arbitrarily weighting indicators of various time horizons by employing monthly frequencies of various modes in their latent-class cluster analysis. Vij et al. (2017) employed a latent-class choice model to estimate unobserved modal preferences of individuals, which they define as "behavioral predisposition towards a certain travel mode or set of travel modes that an individual habitually uses" (p. 242). In brief, although a wide range of measurement techniques is available in the literature, researchers of millennials' travel behavior have not employed many of them yet. In particular, more complex approaches that capture the multidimensional nature of travel modality have been rarely used.

The objectives of this chapter are two-fold. First, I examine various types of multimodality and their relative shares in a sample of millennials and members of Generation X by employing a rich set of variables, including individual attitudes and the use of shared mobility services – these variables are rarely available in conventional travel-diary data. Second, I analyze the effects of various individual attributes, such as socioeconomics and demographics, attitudes and preferences, and residential location, on the likelihood of belonging to certain traveler groups.

4.2 Results

To capture various patterns of travel multimodality, I employed a subsample of 1,070 cases who regularly commute either to work or school, and constructed several indicator variables from their frequency of using various transportation modes for *commute* and *leisure/shopping/social* (henceforth, “non-commute”) trips. For commute trips, the survey asked the frequency of using various modes for one-way trips. Unlike previous studies, I analyze multimodality in a way that takes into account trip purposes, because reports and statistics suggest that millennials’ mode choice may differ from that of older birth cohorts only for trips with certain purposes, e.g., non-commute (Jaffe, 2013, 2014). The original raw data include frequencies of using 13 travel modes reported on a 7-point ordinal scale separately for the two categories of trip purposes. For each of the 26 mode/purpose combinations, individuals marked a choice that ranges from “Not available” to “5 or more times a week.” For analysis, I grouped the 26 variables into nine indicators based on similarity and uniqueness of modes and purposes and developed “monthly” frequencies for four groups of modes for commute trips and five groups of modes for non-commutes. The four groups of modes common to both commute and non-commute trips are: *car as a driver*, *car as a passenger* (including taxi and ridehailing services for commute trips, which are classified separately for non-commute trips), *public transit* (including both bus and rail options), and *active modes* (including walking, biking and skateboarding). An additional group of modes was included for non-commutes, measuring the use of *emerging transportation modes* (ride-hailing services such as Uber/Lyft and carsharing services such as Zipcar/Car2Go) (Table 8). To obtain the monthly frequencies for these nine groups, I summed proxy values that capture the monthly frequencies of the raw modes that belong to each group (Table 9). Given that many studies analyzed the NHTS datasets, which lack information on use of various modes for more than a day, the indicators capturing monthly use of various travel modes are expected to reveal unexplored patterns of multimodality, which may substantially differ from those measured only on one day.

Table 8 Modes in the Survey and Classified Modes for Analysis

Mode in the survey (in the order in the survey)	Classified mode	
	Commutes	Non-commutes
Drive alone	Car as a driver	Car as a driver
Carpool or vanpool, as a driver	Car as a driver	Car as a driver
Carpool or vanpool, as a passenger	Car as a passenger	Car as a passenger
Drive a vehicle from a carsharing program (e.g. Zipcar)	(Not asked)	Emerging modes
Motorcycle or motor-scooter	Car as a driver	Car as a driver
Work/school-provided bus or shuttle	Public transit	(Not asked)
Public bus	Public transit	Public transit
Light rail/tram/subway (e.g. BART, LA Metro)	Public transit	Public transit
Commuter train (e.g. Amtrak, Caltrain, Metrolink)	Public transit	Public transit
Taxi	Car as a passenger	Car as a passenger
Uber/Lyft (or other on-demand ride services)	Car as a passenger	Emerging modes
Bike or e-bike	Active modes	Active modes
Skateboard, scooter, skates	Active modes	Active modes
Walk	Active modes	Active modes

Note: In the survey, the use of carsharing was not asked for commute trips, and work/school-provided bus or shuttle was not asked for non-commute trips.

Table 9 Proxy Values for the Monthly Frequency

Option in the survey	Proxy for the monthly frequency
Not available (not asked for non-commute trips)	0
Available but I never use it ("Never" for non-commute trips)	0
Less than once a month	0.5
1-3 times a month	2
1-2 times a week	6
3-4 times a week	14
5 or more times a week	20

Note: Since non-commute trips often take place outside of one's own neighborhood, respondents do not have the option of "Not available" for each of the 13 raw modes for non-commute trips. Also, one month is assumed to have four weeks, for the purposes of computing the monthly frequencies.

After testing several alternatives, I chose the five latent-class solution as best, based on several goodness of fit measures and interpretability. Although four information criteria (AIC, AIC3, BIC, and sample-size adjusted BIC) kept decreasing and the log-likelihood continued to increase with an increase in the number of classes, I chose the solution with five classes because it reveals a sufficient level of heterogeneity across classes while avoiding unnecessarily complex differentiation among classes and smaller expected class sizes. The smallest class consists of 1.3% of the sample, suggesting the class may capture some outliers in the sample. However, I chose to identify them as a separate class because they appear to represent those millennials who are frequent users of emerging transportation services. In addition, after testing the local independence assumption, I allowed bivariate residual correlations between indicators of different groups of modes for the same trip purposes. In some cases, I also allowed the indicators of the same group of modes for different trip purposes to be correlated (e.g., use of public transit for commute and non-commute trips) (Table 10).

Table 10 Bivariate Residual Correlation Estimates

mode/purpose 1	mode/purpose 2	correlation estimate	two-tailed p-value	sig.
Commute by driving	Commute by active modes	-2.460	-3.474	***
Commute by driving	Leisure trip by driving	25.700	8.436	***
Commute as a passenger	Leisure trip as a passenger	4.034	4.076	***
Commute by public transit	Leisure trip by public transit	4.240	4.748	***
Commute by active modes	Leisure trip by public transit	1.360	2.218	**
Commute by active modes	Leisure trip by active modes	0.291	2.519	**
Commute by active modes	Leisure trip by emerging modes	3.360	3.855	***
Leisure trip by driving	Leisure trip by active modes	0.347	1.812	*
Leisure trip as a passenger	Leisure trip by emerging modes	1.441	1.793	*
Leisure trip by public transit	Leisure trip by active modes	0.397	3.995	***
Leisure trip by public transit	Leisure trip by emerging modes	1.892	3.061	***
Leisure trip by active modes	Leisure trip by emerging modes	0.526	3.076	***

Note: All possible pairs of bivariate residual correlations are tested and only those pairs that are statistically significant at least at the 90% confidence level are included. (*** indicates significant at the 99% confidence level, ** at the 95% confidence level, and * at the 90% confidence level)

4.2.1 Five Traveler Groups

I identified five traveler groups, having different frequencies of use of various travel modes for two trip purposes (Figure 5). In this section, I briefly introduce the multimodal travel patterns and socioeconomic attributes of these classes: monomodal drivers (including 84.7% of cases in the weighted sample), active travelers (8.8%), multimodal drivers (2.9%), transit riders (2.3%), and multimodals for leisure (1.3%). To understand the distinctive traits of each traveler group, I use both active and inactive covariates.

Containing the vast majority of cases, ***monomodal drivers*** drive for most of their commute (16.3 times per month) and non-commute (12.8 times per month) trips. Monomodal drivers own the most vehicles and have the greatest access to their household's vehicles (available 92.0% of the time). The majority of monomodal drivers are full-time workers (71.2%), usually with either an associate's or bachelor's degree (38.6% and 36.3%, respectively), and their commute distance is the longest among the five groups. Most monomodal drivers tend to live with their own children and have household incomes between $60,000 and $120,000. The members of this group are older, are more likely to perceive that having a car is a necessity, and more often reside in suburban or exurban neighborhoods. As expected, they drive the most (146.3 miles per week), which is six times the average driving distance for transit riders.

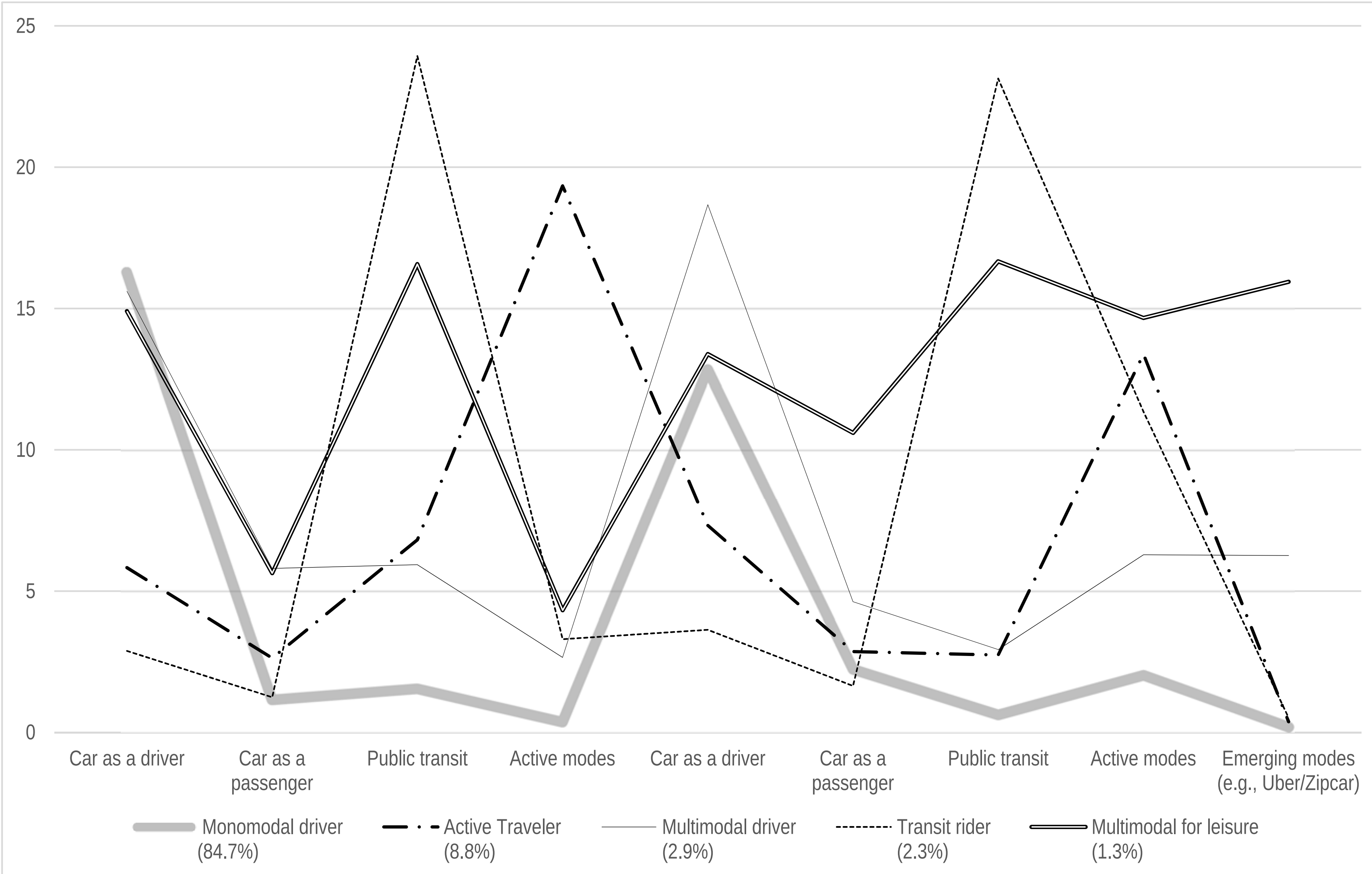


Figure 5 Monthly Frequencies of Use of Travel Modes for Commute (First Four) and Non-Commute (Second Five) Trips by Class

The ***active travelers*** travel most frequently by walking, biking or skateboarding for both commute (19.3 times per month) and non-commute (13.4 times per month) purposes. Most active travelers (71.9%) do not hold a driver's license, they own few household vehicles (0.64 per adult), and report lower car availability (51.9%) than the other groups except transit riders. Active travelers reveal the most pragmatic attitudes towards cars, they have the most positive attitudes towards exercise, and (interestingly) have the highest preference for in-store shopping compared to online alternatives.[2] Two of every three members of this group are millennials (69.5%), and their share of urban residents is the second highest (42.4%) after the multimodal drivers (68.2%).

Even if ***multimodal drivers*** usually drive, they sometimes also commute as a passenger in a car driven by someone else, either via carpool, a taxi, or on-demand ride services (5.8 times per month, or more than once a week). For non-commute trips, they tend to drive instead of having others drive for them (18.7 versus 4.6 times per month). Multimodal drivers have the most commute days per week among all groups (5.4 days a week), and they likely work full time, with a majority of them having a driver's license and a car available 90% of the time. Multimodal drivers feel more constrained to drive, for reasons such as their inflexible schedules or destinations not served by public transit. Interestingly, they value active modes more than any other group, and they report higher variety-seeking preferences. Their residential neighborhoods have a higher land-use mix, and two thirds of them live in urban areas. Multimodal drivers' preferences and residential

[2] This might be unexpected in view of the preponderance of millennials in this group. However, this result appears to be driven by the substantially stronger preference for in-store shopping on the part of the *Gen X* members of this group (compared to Gen X members of the other groups), whereas the preference for in-store shopping by the millennials in this group does not differ substantially from that of millennials in other groups, and is much lower (average factor score -0.07) than that of the Gen Xers (0.32) in the group.

location appear to explain their weekly vehicle-miles driven (VMD), which are 37 percent fewer than those of monomodal drivers.

Transit riders use public transit almost every day for commute (23.9 times per month) and non-commute (23.1 times per month) trips. For non-commute trips, they often travel by active modes, possibly as an access or egress mode for public transit, because they lack access to a car (e.g., only 39.2% of the members of this class hold a driver's license, and on average they own the fewest vehicles per adult in the household). Not surprisingly, this group has the largest share of transit pass holders (83.1%). They contain the largest share of college graduates and current students (38.3% of this group being either part-time or full-time students). On average, transit riders have the lowest household income (74.7% of this group earning less than or equal to $60,000). Also, this group shows high support for environmental policies that would regulate driving. The members of this class do not own many vehicles, but are highly educated. About one fifth of transit riders reside in neighborhoods located in the central core of cities such as downtown Los Angeles and San Francisco, where residents experience good public transit services. As a result, they drive the fewest miles (23.3 miles per week, on average).

As the smallest among the five traveler groups (including only 1.3% of the 1,070 cases in the sample, i.e. 14 people), the ***multimodals for leisure*** reveal a unique pattern of mode use, which popular media depict as stereotypical of millennials. Their total numbers of commute and non-commute trips are the highest among all classes, implying that either their trip rates are the highest or (more likely) they tend to use multiple modes for a single tour. Interestingly, although they either drive or take public transit for their commute, for non-commute trips they use all modes in similar frequencies. Compared to the other groups, multimodals for leisure are heavy users of emerging transportation modes such as Uber/Lyft and Zipcar for non-commute trips, telecommute the most, and often have graduate degrees. About 40% of individuals in this class earn more than $120,000 a year, and they feel they are well established in their life. Although they predominantly live in the suburbs and expect to stay there in the long run, multimodals for leisure do not think the car is a necessity, and strongly support pro-environmental transportation regulations. They report that they are materialistic and, interestingly, 80% of them are millennials (most of them are independent millennials who have already established their households or live with their partner). Although these young professionals seem to be the stereotypical millennial, their share in the sample is the smallest. Even though they travel by various modes, their average weekly VMD is almost as high (136.6 miles) as that of monomodal drivers (146.3 miles). Their economic resources (reflected by their high household incomes) and lifestyles (including materialism) appear to explain their unique travel patterns.

4.2.2 Class Membership Model

In addition to depicting the five classes of travelers based on summary statistics, I attempt to understand the factors affecting the probabilities of individuals belonging to these groups. Table 2 presents the estimates of active covariates that are statistically significant in the membership model. Here, the reference group is monomodal drivers (which is therefore omitted in the table), so I interpret the coefficients for the other groups in comparison to monomodal drivers. I test two hypotheses by including covariates that relate to millennials' limited economic resources and delayed life course events, as well as to their different preferences from the older cohorts. Moreover, I analyze the separate effects of the built environment, which most studies neglected.

Economic factors and related living arrangements affect class membership in various ways. First, not surprisingly, those without a driver's license are more likely to be either transit riders or active travelers than monomodal drivers. Fewer cars/adult in the household is associated with belonging to transit riders. Those who earn less than $60,000 a year are more likely to be transit riders than monomodal drivers. People living without a partner and who do not have any own children living at home are more likely to be active travelers. Also, those with higher educational credentials are associated with a higher likelihood of using public transit. However, these factors do not present the full picture of millennial multimodality. I also find separate effects of individual ***attitudes and preferences***. In particular, those who think of a car as a mere "tool" (to reach a destination) rather than a desirable object in its own right are more likely to be transit riders or active travelers than monomodal drivers. Those who share concerns over the environmental impacts of driving tend to travel more by public transit or active modes. Interestingly, pro-store shopping preferences are associated with being more multimodal.

Land use attributes of one's place of residence help account for multimodality. Activity intensity, a composite measure extracted from a factor analysis on variables such as population and employment density in the place of residence, increases the likelihood of an individual being a public transit user. Dense neighborhoods, mostly located in or close to the central city, usually offer a transit-conducive environment and are well served by public transit. Land-use balance, a composite index measuring the balance between housing and employment, facilitates residents being multimodal. Note that multimodal drivers are the second most frequent users (after the multimodals for leisure class) of emerging transportation modes (they use Uber/Lyft or Zipcar for an average of 6.3 times a month as of fall 2015), and two thirds of them live in urban neighborhoods with more balanced land use mixes.

Table 11 Sample Characteristics for the Indicators and Covariates, by Traveler Group (Sample Size N=1,070)

(N=1,070 commuters)	Monomodal driver (84.7%)	Active traveler (8.8%)	Multimodal driver (2.9%)	Transit rider (2.3%)	Multimodal for leisure (1.3%)
Frequency per month					
For commuting trips					
Car as a driver	16.3	5.8	15.6	2.9	14.9
Car as a passenger	1.2	2.6	5.8	1.2	5.6
Public transit	1.6	6.8	5.9	23.9	16.6
Active modes	0.4	19.3	2.7	3.3	4.3
Total	19.4	34.6	30.0	31.4	41.4
For leisure trips					
Car as a driver	12.8	7.3	18.7	3.6	13.4
Car as a passenger	2.2	2.9	4.6	1.6	10.6
Public transit	0.6	2.7	2.9	23.1	16.7
Active modes	2.0	13.4	6.3	11.4	14.7
Emerging modes	0.2	0.4	6.3	0.5	15.9
Total	18.0	26.7	38.8	40.3	71.3
Active covariates					
Travel pattern and mobility choices					
# of commute days per week	4.5	4.6	5.4	4.9	3.1
Commute distance	9.2	3.5	6.3	4.3	6.9
Telecommuting frequency					
0~1 times per week	74.4%	67.8%	70.1%	77.4%	78.0%
2~3 times per week	12.6%	12.2%	24.2%	5.2%	0.9%
4~6 times per week	12.9%	20.0%	5.7%	17.4%	21.0%
Having a driver's license	95.0%	71.9%	100.0%	39.2%	97.4%
Cars per household adult	0.90	0.64	0.75	0.40	0.70
Household composition					
Household size	3.24	3.17	2.97	3.24	2.89
Living with parents	24.5%	29.7%	21.2%	1.8%	6.8%
Living with parents (of millennials)	39.9%	31.7%	34.8%	2.3%	8.5%
Living with partner	64.4%	36.8%	74.9%	41.1%	76.4%
Living with own children	51.0%	23.5%	31.8%	41.9%	33.5%
Student/worker status and educational attainment					
Part-time student	10.4%	12.1%	0.6%	15.9%	0.0%
Full-time student	11.7%	8.6%	4.4%	22.4%	16.3%
Part-time worker	21.0%	47.1%	15.2%	19.4%	10.8%
Full-time worker	72.1%	47.1%	84.2%	60.1%	79.9%
Some college	38.6%	40.4%	20.6%	32.2%	22.7%
Bachelor's degree	36.3%	18.4%	28.3%	44.2%	5.9%
Graduate degree	16.5%	14.7%	22.2%	10.3%	56.9%
Annual household income					
Less than $60,000	39.1%	49.9%	57.8%	74.7%	39.7%

Table 11 continued

(N=1,070 commuters)	Monomodal driver (84.7%)	Active traveler (8.8%)	Multimodal driver (2.9%)	Transit rider (2.3%)	Multimodal for leisure (1.3%)
$60,000 - $120,000	36.0%	36.0%	11.7%	25.3%	20.4%
More than $120,000	24.9%	14.2%	30.4%	0.0%	39.9%
Attitudes and preferences (factor scores)					
Long-term suburbanite	0.171	-0.359	0.049	-0.158	0.365
Must own a car	0.082	-0.427	0.075	-0.402	-1.520
Car as a tool	-0.039	0.178	-0.011	0.109	-0.531
Materialism	0.071	0.162	0.395	0.257	0.573
Pro-environmental	0.022	0.632	1.051	0.901	1.261
Time/mode constrained	0.163	-0.346	0.839	-0.402	-0.274
Pro-exercise	0.137	0.168	-0.095	-0.448	-0.458
"I like biking" [a]	0.046	0.231	0.294	-0.058	0.444
Variety seeking	0.094	0.225	0.493	0.279	0.293
Established in life	0.275	-0.005	-0.019	0.265	0.519
Pro-store-shopping	-0.088	0.357	-0.055	0.115	-0.438
Overall rating of travel mode					
Cars (1~5)	4.3	3.6	4.5	3.6	4.0
Public transit (1~5)	2.7	3.5	3.7	4.1	3.7
Active modes (1~5)	3.1	4.1	4.4	3.6	4.0
Land use attributes					
Activity intensity	0.101	0.399	0.768	0.849	0.329
Balance of various land uses	0.196	0.252	0.818	0.666	-0.364
Transit service quality	10.2	15.5	26.0	27.0	8.2
Inactive covariates					
Demographics					
Age	34.4	31.0	28.9	34.7	31.6
Proportion of millennials	50.6%	69.5%	78.4%	43.0%	80.2%
Mobility choice					
Having a transit pass	10.9%	29.8%	20.2%	83.1%	45.0%
Car availability [b]	92.0%	51.9%	89.4%	37.9%	52.9%
Self-reported weekly VMD	146.3	47.1	92.5	23.3	136.6
Residential neighborhood type					
Central city	1.3%	6.4%	14.5%	21.6%	0.0%
Urban	20.4%	42.2%	68.2%	41.5%	28.4%
Suburban	48.0%	35.7%	13.3%	23.2%	47.8%
Exurban	21.4%	9.7%	2.2%	13.7%	10.7%
Rural	9.0%	6.0%	1.8%	0.0%	13.1%

Notes: **Bold** values indicate the highest value for each row; [a] denotes a single-item response (and not a factor score) for this attitudinal variable; [b] measures a self-reported car availability (0-100%), i.e. the percentage of time an individual has access to a private vehicle.

Table 12 Class Membership Model (N = 1,070; Reference: Monomodal Drivers (84.7%))

Covariates	Active traveler (8.8%)	Multimodal driver (2.9%)	Transit rider (2.3%)	Multimodal for leisure (1.3%)
Travel pattern and mobility choices				
Natural log of commute distance	-1.295***	-0.223	-0.229	-0.486
# commute days per week	0.295*	0.587***	1.154***	-0.206
Telecommute (reference: 0-1 per week)				
Telecommute 2-3 times per week	0.106	0.629	-0.663	-2.327
Telecommute 4-6 times per week	1.054**	0.217	2.406**	1.769
Has a drivers' license	-1.921***	10.287***	-4.923***	2.21
Cars per adult in the household	-0.673	0.234	-1.113*	-0.459
Household characteristics				
Household size	0.138**	-0.265	0.278	-0.454
Living with a partner	-0.69*	1.178**	-0.766	1.365
Living with own children	-1.172**	-1.564**	-0.474	-0.675
Student status (reference: not a student)				
Part-time student	-0.668	-3.483**	1.257	-16.847***
Full-time student	-2.347***	-0.523	-0.206	1.19
Educational attainment (reference: up to high school)				
Some college	-0.008	-1.949*	-0.826	0.642
Bachelor's degree	-0.838	-1.661	0.771	-1.174
Graduate degree	-0.246	-1.693	2.466**	1.362
Annual household income (reference: below $60,000)				
$60,000 - $120,000	0.202	-2.088***	-1.916**	-1.974
More than $120,000	0.658	0.69	-19.546***	-0.973
Attitudes and preferences				
Long-term suburbanite	-0.335**	0.362	0.462	0.654
Must own a car	-0.149	0.326	0.059	-1.1*
Car as a tool	0.405**	-0.119	0.709***	-1.213***
Materialism	0.259	0.172	-0.267	0.772**
Pro-environmental	0.298*	1.074***	0.746**	0.592
Time / mode constrained	-0.412**	0.487**	-0.42	-0.527
Pro-exercise	0.075	-0.499**	-0.671**	-0.999***
I like biking[(a)]	0.126	-0.444	-0.251	1.061*
Variety seeking	0.582***	0.406	0.07	-0.006
Established in life	-0.176	-0.43	0.88***	0.207
Pro-store shopping	0.547***	-0.956***	0.805***	-0.602
Overall rating for cars	-0.834***	0.161	-0.056	0.085
Overall rating for public transit	0	0.381*	1.355***	0.064
Overall rating for active modes	1.064***	1.375***	0.308	0.553
Land-use attributes				
Activity intensity	-0.076	-0.36	1.744**	-0.585
Land-use balance	-0.085	0.474**	0.587**	-0.885***
Transit service quality	0.015	0.099***	0.065**	0.009

Notes: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level; [(a)] denotes a single-item response (and not a factor score) for this attitudinal variable.

4.2.3 Generational Effects

To evaluate the effects of being a member of a certain generation on the adoption of multimodality, I control for one's age as an inactive covariate in the latent profile analysis, to investigate *subtler* differences among individuals belonging to the various groups (i.e., how they differ within and across generations). In fact, many studies attempted to measure generational effects by including a set of binary variables that indicate whether individuals are millennials or members of preceding generations in multiple regression models (Buehler & Hamre, 2014; McDonald, 2015). This approach may be effective for checking the existence of such effects, especially with panel or repeated cross-sectional datasets; however, it cannot reveal specific sources of the effects unless a rich set of qualitative attributes is also included. In contrast, I hypothesize that individuals' sociodemographic and economic conditions, living arrangements, and attitudes and preferences affect the type and intensity of travel multimodality. For instance, two same-aged people may travel in different ways because of the aforementioned factors being different (e.g., married or not), and two people with different ages may be very similar in their multimodal patterns, because of these factors being similar (e.g., similar preferences for urban lifestyles and active modes).

Figure 6 displays the share of each traveler group by age (note that the y axis starts at 78 percent to clearly present the variation in the composition by age). Since I do not have sufficient cases for each age, I calculate five-year moving averages. As expected (in view of their large share), monomodal drivers dominate all age groups from 17-20 to 47-51; however, I see gradual changes, or even fluctuations, in the shares of the five traveler groups by age. The proportion of active travelers tends to decrease up to the age of 40 and slightly increase again after that age (probably because of the reduction in household obligations as children become older). Transit riders first peak around 20 years old, gradually decrease to 0.5% at about 33 years old, and rebound among individuals older than 45. Given that Figure 3 presents a one-time snapshot of the population, not a trajectory that follows the same individuals over time, young transit riders and older transit riders may differ in their characteristics. The largest proportion of multimodals for leisure is observed around an age of 26 years. In sum, treating one's age as an inactive covariate in the latent-class cluster analysis helps reveal nuanced, continuous, distributions of heterogeneity in multimodality by age, while I use individual attitudes and preferences, in addition to socio-demographics, to characterize the mobility styles of the members of the various latent classes. Still, how many millennials will continue to have multimodal travel patterns (as opposed to travel patterns similar to those of the current older adults) as they age is an open question, which cannot be answered with the analysis of cross-sectional data.

4.3 Discussion

In this chapter, I employs a latent-class model and a comprehensive set of variables to identify the varying patterns of travel multimodality and the relationships of these patterns and individual attributes. By doing so, I reveal multiple classes of multimodal travelers. The results suggest possible changes in the mode use patterns of millennials in the coming years, which can inform policies that help millennials stay multimodal.

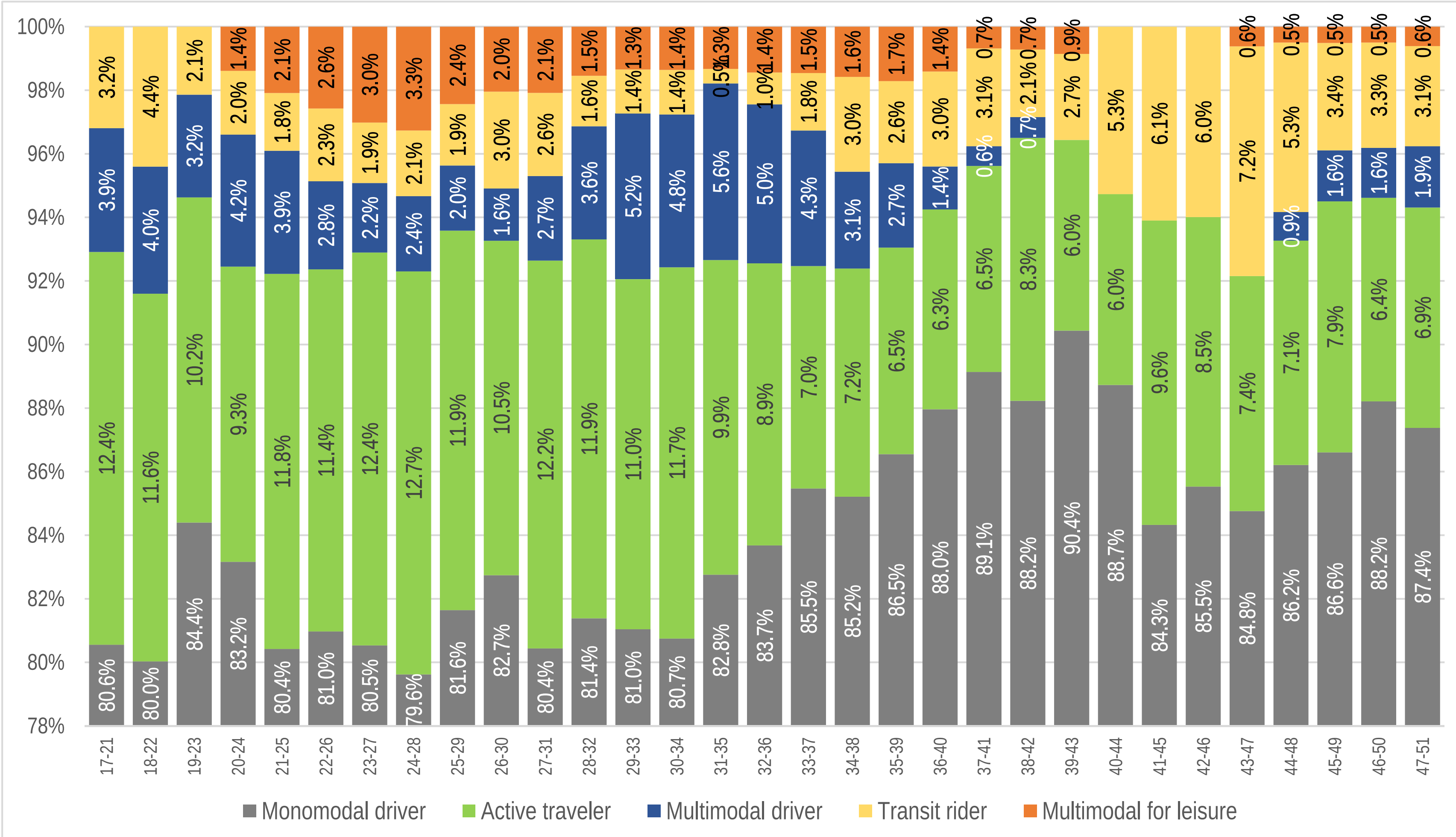


Figure 6 Shares of Five Traveler Classes by Age Group

* Each bar presents the traveler group shares for cases within the specified five-year age range, with each bar advancing the five-year window by one year. From the bottom to the top, each bar respectively presents the shares of monomodal drivers, active travelers, multimodal drivers, transit riders, and multimodals for leisure.

Unlike popular images of multimodal millennials in the media, this chapter (Figure 6) shows that the majority of millennials are monomodal drivers, which is consistent with a previous study (K. M. Ralph, 2017). In contrast to the monomodal drivers, multimodal drivers,although they have similar driver's licensure rates and car availability, choose driving for only half of their trips and drive 37% fewer miles on a weekly basis. These two groups differ by several individual characteristics including household income, childbearing, and personal preferences. Multimodal drivers more often reside in urban neighborhoods with mixed land uses (e.g., stores and restaurants located in close proximity to their home), where public transit and non-motorized modes are viable alternatives. That is, land use facilitates, or inhibits, multimodality. Related to this, the share of multimodal drivers diminishes and that of monomodal drivers increases among individuals between 33 and 40 years old, an age in which people undergo marriage and childbearing, achieve increases in their earnings, and often relocate to the suburbs. Thus, to encourage individuals to maintain environmentally-beneficial behaviors and higher levels of travel multimodality, planners may take two approaches. First, they can spearhead plans for affordable residential alternatives (with decent public school quality) in the central parts of cities for those who *prefer* urban lifestyles, but also want to buy a home and raise children. Second, they can design and plan some suburbs with urban amenities (e.g., land-use mix) for those who relocate, to make their travel behavior more sustainable.

For "multimodal millennials" enthusiasts, it may be disappointing to see that the three "desirable" traveler groups – transit riders, active travelers, and multimodal drivers – only account for 14% of the cases in the entire sample, and 17.7% of the subsample of millennials. Still, on average, millennials have a larger share of these traveler groups than the members of Generation X. Also, the membership model reveals that not only economic factors but also attitudes and preferences explain the likelihood of an individual to adopt travel multimodality (as shown in Table 12). Thus, the current shares of the five traveler groups by age are likely to change in the future as millennials age and experience life course events (even if at a more delayed time in life), assuming they maintain their current attitudes and preferences (e.g., they are more supportive of environmental policies and more committed to physical activities).

As for effective policies and interventions that encourage multimodality, I suggest focusing on the *dynamic* nature of multimodality, which helps identify windows of opportunity during which individuals adjust their travel patterns to new social and physical environments (Scheiner et al., 2016). For example, planners and policymakers may focus on certain millennial subgroups (e.g., recent movers) or those millennials in certain parts of a region (e.g., walkable districts well served by public transit). By providing information on feasible alternatives that meet (parts of) millennials' travel demand, I can expect millennials to keep being multimodal for longer in their life, and to continue their behavioral patterns in future years.

In this chapter, I analyze cross-sectional data, which does not observe historic trends, so it cannot estimate the extent to which today's millennials will behave in coming years in the same way today's Gen Xers do. To overcome this limitation, the research team are completing a second round of data collection with a larger sample, which includes some of the same individuals from the first survey as well as new respondents included to refresh the panel. With the two waves collected at a two-and-a-half-year interval, I plan to investigate the *dynamic* nature of multimodal travel patterns of the same individuals by employing a latent transition model. By the time of the second survey, these individuals are likely in a different life stage, they may have different attitudes and preferences, the environments in which they live may have changed, while the quality of emerging transportation technologies and services may have substantially evolved in the meantime. Examining the ways that these various types of changes affect the travel multimodality of these individuals will help us better understand behavioral changes and produce practical insights for planning and policy.

CHAPTER 5. THE IDENTIFICATION OF HETEROGENEOUS RESIDENTIAL PREFERENCES AMONG MILLENNIALS AND THE MEMBERS OF GENERATION X IN CALIFORNIA: A LATENT-CLASS APPROACH

5.1 Introduction

In the millennial literature on the factors affecting the travel behaviors and mobility choices of millennials (Delbosc & Ralph, 2017), one fundamental factor underlying millennials' everyday decisions has not been studied very much. That is, people make various travel-related choices conditional on the attributes of their residence, workplace/school, or places they frequently visit (Mokhtarian & Cao, 2008). For example, several studies suggest that millennials are economically constrained to and culturally oriented towards the use of active modes. However, if they do not live in residential locations that support active modes of travel, they may not be able to walk, bike, or ride public transit. Thus, it is important to better understand the way millennials choose their residential location and the reasons for which they do so, instead of explaining their travel behaviors *as if* their home locations were exogenously given.

To address the current research gap, in this chapter, I model the residential location choice of millennials and the members of the preceding Generation X (Gen Xers), while accounting for taste heterogeneity in the population, through the estimation of a latent-class choice model (LCCM). In this chapter, I hypothesize that individuals have heterogeneous preferences for neighborhood attributes. Then, I assume that the population consists of several unobserved groups whose members share homogenous preferences within each group, but present heterogeneous preferences across groups. In doing so, instead of *deterministically* assigning individuals to each group (e.g., as I would do using a k-means clustering approach), I *probabilistically* classify them into latent groups. I analyze the factors that explain group membership (including economic constraints, delayed life course events, and attitudes on various dimensions) and present the distribution of these groups by age and geography. By doing so, I expect to shed light on a fundamental choice of millennials, which could also indicate what sustainable development patterns and transportation solutions are desired in coming years.

5.2 Results

To represent the location choice context of individuals, I first filter out those without precise home and work/school addresses, non-commuters, and millennials living with parents, leaving 729 valid cases (363 millennials and 366 Gen Xers). Next, I generate their choice set by combining the chosen neighborhood with nine unchosen alternatives that are randomly selected within an estimated search radius from their work or school. To estimate the search radius, which varies by individual, I conduct survival analysis by modeling the commute distance t with $\ln t = \mathbf{x}'\beta + u$, in which u follows a gamma distribution whose two parameters are estimated simultaneously with β. I take the 95th percentile of u (based on the estimated parameters of its distribution), add it to $\mathbf{x}'\beta$, and exponentiate the result (to reverse the log-transform) to obtain the search radius. For the small number of cases (5% of our sample) whose actual commute distances are longer than their 95th percentile estimates, I use their actual commute distances plus 0.1 mile as their search radius. The survival model includes socioeconomic and demographic characteristics as explanatory variables and the network-derived commute distance as its dependent variable (Tables 13, 14, and 15). For the latent class choice model, I tested various numbers of latent classes and numerous model specifications with explanatory variables as either neighborhood attributes in the choice model or active covariates in the membership model. Finally, I chose a three-class solution based on goodness-of-fit measures and interpretability (Table 16). I first provide details on the members of the three latent classes with the membership model outcome and the profile table (Tables 17 and 18). Then, I examine their heterogeneous residential preferences with the choice model outcome (Tables 19 and 20).

5.2.1 Membership Model

Table 17 presents the coefficient estimates of the active covariates in the membership model, and Table 18 displays the (probability-weighted) class-specific averages of various active/inactive covariates. These covariates include individual and household level socioeconomic and demographic characteristics and three attitudes.

The ***younger, pro-urban*** class: This class consists of 53% of the sample. About two thirds of this class are millennials, and about 40% of its members live in either central city or urban neighborhoods. Some distinctive characteristics of this class include: about three quarters having some or full college education, living with 0.38 children under 6 on average, 20% studying either full-time or part-time, 76% working full-time (compared to 90% of the next class, *affluent, highly educated*), about one half earning less than or equal to $60,000 a year, only one third owning their homes, having the lowest average factor score for *pro-suburban lifestyles* among the three classes, and presenting a relatively high average factor score for *pro-environmental policies*. Interestingly, the members of this class do not necessarily perceive the car (merely) as a tool, which appears at odds with the popular notion of millennials as a carless generation (the statements with the highest loadings on this factor are: "*To me, a car is just a way to get from place to place.*" and "*The functionality of a car is more important to me than its brand*"). Qualitative studies indicate that today's young adults often associate the acquisition of a driver's license and access to cars with maturity, employability, freedom, and full adulthood, but not always with a status symbol or self-expression (Delbosc & Currie, 2014; Hopkins, 2016). Thus, millennials, especially in this class, who value cars for non-practical reasons may not necessarily become habitual drivers, even when their situation allows it.

Table 13. Descriptive Statistics of the Commuter Sample (weighted, n=729)

Explanatory variable	All (n=729)	Millennials (n=363)	Gen Xers (n=366)
Race/ethnicity			
non-Hispanic: White	45.2%	41.5%	48.5%
non-Hispanic: African American	3.3%	1.4%	5.0%
non-Hispanic: Asian	14.6%	14.3%	14.9%
non-Hispanic: Other races	2.4%	1.3%	3.4%
Hispanic	34.4%	41.5%	28.2%
Age	35.0	27.8	41.4
Work/study status			
Full-time worker	81.1%	76.2%	85.5%
Part-time worker	14.4%	16.0%	12.9%
Full-time student	4.1%	7.5%	1.1%
Part-time student	0.4%	0.2%	0.5%
Educational attainment			
Less than high school	0.9%	1.2%	0.6%
High school/GED	8.8%	10.6%	7.3%
Some college/technical school	22.0%	22.5%	21.6%
Associate's degree	11.8%	11.7%	11.9%
Bachelor's degree	37.2%	38.4%	36.1%
Graduate degree (e.g., MS, PhD, MBA)	13.6%	11.1%	15.9%
Professional degree (e.g., JD, MD, DDS)	5.7%	4.5%	6.7%
Living with own child(ren)	54.9%	41.7%	66.6%
Annual household income			
Up to $20,000	7.2%	10.7%	4.1%
$20,001 to $40,000	15.6%	21.2%	10.7%
$40,001 to $60,000	15.5%	18.8%	12.6%
$60,001 to $80,000	15.2%	14.6%	15.8%
$80,001 to $100,000	11.4%	9.7%	13.0%
$100,001 to $120,000	11.7%	9.7%	13.5%
$120,001 to $140,000	6.9%	6.0%	7.7%
$140,001 to $160,000	6.8%	4.5%	8.8%
More than $160,000	9.6%	4.9%	13.8%
Housing tenure			
Own	48.5%	30.5%	64.4%
Rent	49.2%	67.2%	33.3%
Provided by others	2.3%	2.3%	2.3%
Car per household driver	0.95	0.92	0.97
ln(Regional access (# of jobs in 45 minutes by driving))	12.14	12.21	12.07

Table 14. Survival Model Outcome (*dep*: Network Commute Distance, weighted, n=729)

Explanatory variable	Estimate	Standard errors	Chi-Square	Pr > Chi-Square
Race/ethnicity (reference: non-Hispanic White)				
non-Hispanic: African American	0.360	0.006	3,259.82	<.0001
non-Hispanic: Asian	0.180	0.003	2,826.91	<.0001
non-Hispanic: Other races	-0.146	0.007	390.55	<.0001
Hispanic	0.075	0.003	839.79	<.0001
Age	0.007	0.000	2,128.70	<.0001
Work/study status (reference: full-time student)				
Full-time worker	0.225	0.006	1,343.38	<.0001
Part-time worker	0.175	0.006	772.92	<.0001
Part-time student	0.057	0.019	9.26	0.0023
Educational attainment (reference: less than high school)				
High school/GED	0.196	0.012	253.61	<.0001
Some college/technical school	0.217	0.012	329.83	<.0001
Associate's degree	0.587	0.012	2,330.67	<.0001
Bachelor's degree	0.251	0.012	436.79	<.0001
Graduate degree (e.g., MS, PhD, MBA)	0.075	0.012	37.12	<.0001
Professional degree (e.g., JD, MD, DDS)	-0.153	0.013	140.95	<.0001
Living with own child(ren)	-0.113	0.003	1,925.01	<.0001
Annual household income (reference: up to $20,000)				
$20,001 to $40,000	0.219	0.005	1,798.43	<.0001
$40,001 to $60,000	0.313	0.006	3,261.12	<.0001
$60,001 to $80,000	0.391	0.006	5,086.63	<.0001
$80,001 to $100,000	0.411	0.006	4,725.19	<.0001
$100,001 to $120,000	0.495	0.006	6,629.87	<.0001
$120,001 to $140,000	0.713	0.007	11,651.10	<.0001
$140,001 to $160,000	0.597	0.007	7,722.99	<.0001
More than $160,000	0.631	0.007	9,502.38	<.0001
Housing tenure (reference: own)				
Provided by others	-0.392	0.008	2,659.04	<.0001
Rent	-0.316	0.003	13,734.80	<.0001
Car per household driver	0.126	0.003	1,497.13	<.0001
ln(Regional access (# of jobs in 45 minutes by driving))	0.015	0.001	193.60	<.0001
Intercept	1.059	0.020	2,891.55	<.0001
Scale	0.996	0.001		
Shape	0.458	0.003		

Table 15 Akaike Information Criterion (AIC) of Five Different Distributions to the Survival Model

Model	Log likelihood (LL)	No. of covariates (c)	No. of ancillary parameters (a)	AIC
Exponential	-1278555.77	27	1	2557167.53
Weibull	-1274717.47	27	2	2549492.94
Log-Normal	-1271114.58	27	2	2542287.17
Log-Logistic	-1264851.94	27	2	2529761.87
Generalized Gamma	-1257017.75	27	3	2514095.49
Generalized Gamma(0)[1)]	-1307952.78	0	3	2615911.56

AIC = -2LL + 2(c+a)
1) Null model with no covariates

Table 16 Goodness-of-Fit Measures of Latent Class Solutions

No. of classes	LL	BIC	AIC	AIC3	CAIC	SABIC
1	-1434.6	2984.1	2903.2	2920.2	3001.1	2930.1
2	-1314.6	2973.9	2731.3	2782.3	3024.9	2811.9
3	-1220.0	3014.5	2610.1	2695.1	3099.5	2744.5
4	-1138.1	3080.3	2514.1	2633.1	3199.3	2702.4

No. of classes	No. of parameters (p)	L^2	Degree of freedom	p-value	Reduction in errors(0)	Reduction in errors
1	17	2869.208	844	1.80E-218	0.206	0.205
2	51	2629.263	810	7.40E-191	0.274	0.273
3	85	2440.089	776	3.50E-171	0.326	0.325
4	119	2276.123	742	2.20E-155	0.371	0.370

BIC = -2LL + (log *N*)*p; AIC = -2LL + 2*p; AIC3 = -2LL + 3*p; CAIC = -2 LL [(log *N*) + 1]*p; and SABIC = -2LL + log ((N+2)/24) * p *(N refers to the number of observations.)*

Table 17. Class Membership Model Results with Effect Coding (weighted, n=729)

Class name (share)	Younger, pro-urban (53%)			Affluent, highly educated (32%)			Middle-class homeowners (15%)		
	Coeff.	z-value	sig.	Coeff.	z-value	sig.	Coeff.	z-value	sig.
Intercept	12.18	4.86***		-6.14	-2.82***		-6.04	-3.34***	
Non-Hispanic White									
Yes	0.50	1.29		2.44	3.83***		-2.94	-3.81***	
Educational attainment									
Up to high school	-4.39	-2.76***		1.91	1.32		2.49	1.07	
Some college	6.99	4.45***		-12.14	-4.75***		5.15	3.77***	
Bachelor's degree	-2.92	-3.80***		4.73	4.19***		-1.81	-1.81*	
Graduate school	0.32	0.43		5.50	4.41***		-5.82	-3.82***	
Number of household children[1]									
Below 6	2.75	3.32***		-1.22	-1.61		-1.53	-2.00**	
6 to 11	-11.32	-4.90***		10.15	4.76***		1.16	1.86*	
12 to 17	-1.39	-2.27**		0.10	0.13		1.30	1.70*	
Annual household income									
Less than $60k	-0.67	-1.24		-5.03	-4.50***		5.70	4.31***	
$60k ~ 120k	-3.44	-4.11***		-2.21	-2.83***		5.66	4.22***	
More than $120k	4.11	3.78***		7.25	4.51***		-11.36	-4.48***	
Housing tenure									
Own	-2.26	-4.12***		-3.94	-4.42***		6.20	4.84***	
Car per driver (categorical)									
zero vehicle	11.86	3.24***		-19.14	-3.21***		7.29	1.87*	
Less than one	-7.22	-4.30***		7.98	3.74***		-0.76	-0.55	
one	-1.96	-1.78*		6.73	3.23***		-4.77	-3.05***	
Greater than one	-2.68	-2.16**		4.43	2.20**		-1.75	-1.18	
Attitudes									
Pro-suburban lifestyles	-3.06	-4.75***		-1.34	-2.78***		4.40	4.81***	
"Car as a tool"	-1.45	-3.52***		-2.55	-4.15***		4.00	4.55***	
Pro- environmental policies	1.61	4.10***		-2.22	-4.35***		0.61	1.75*	

* Statistically significant at the 90% level, ** at the 95% level, and *** at the 99% level.
[1] These numbers are counted only for those households living with "own" children

Table 18. Summary Statistics of Latent Classes (weighted, n=729)

	Younger, pro-urban (53%)	Affluent, highly educated (32%)	Middle-class homeowners (15%)	All
Non-Hispanic White	46%	53%	23%	44.6%
Educational attainment				
Up to high school	10%	9%	14%	9.8%
Some college	44%	8%	51%	33.8%
Bachelor's degree	29%	54%	30%	37.1%
Graduate school	17%	29%	6%	19.2%
Number of household children[1]				
Below 6	0.38	0.31	0.28	0.35
6 to 12	0.06	0.83	0.67	0.40
13 to 17	0.09	0.29	0.42	0.20
Annual household income				
Less than $60k	53%	15%	37%	39%
$60k ~ 120k	29%	43%	61%	38%
More than $120k	17%	42%	3%	23%
Housing tenure (own)	30%	60%	89%	48.0%
Cars per driver (categorical)				
Zero vehicles	5%	0%	1%	3%
Less than one	15%	25%	28%	20%
One	69%	63%	65%	66%
Greater than one	11%	12%	7%	11%
Attitudes				
Pro suburban lifestyles	-0.334	0.110	0.722	-0.037
"Car as a tool"	-0.057	-0.240	0.374	-0.051
Pro environmental policies	0.261	-0.100	0.323	0.156
Student status (inactive covariate)				
Part-time student	11%	5%	8%	9%
Full-time student	9%	4%	6%	7%
Work status (inactive covariate)				
Part-time worker	21%	10%	24%	18%
Full-time worker	76%	90%	76%	81%
Average age (inactive covariate)	32.8	37.0	37.7	34.9
Age group (inactive covariate)				
18-24	20%	7%	4%	13%
25-29	21%	12%	11%	16%
30-34	19%	20%	12%	19%
35-39	20%	22%	36%	23%
40-44	10%	19%	10%	13%
45-50	11%	20%	26%	16%
Chosen neighborhood type (inactive covariate)				
Central city	8%	5%	0%	6%
Urban	32%	28%	14%	28%
Suburban	42%	37%	50%	42%
Exurban	12%	20%	25%	17%
Rural	6%	10%	11%	8%

[1] These numbers are counted only for those households living with "own" children.

The ***affluent, highly educated*** class***:*** This class consists of another 32% of the sample. About 39% of this class are millennials, and about one third live in either central city or urban neighborhoods. More than one half are non-Hispanic White, more than 80% earn either a Bachelor's or a graduate degree, 90% are full-time workers, 42% earn a household income more than $120,000 a year, 60% are homeowners, they live with 0.83 child between 6 and 12 on average, and have *ambivalent* preferences for either urban or suburban lifestyles, but likely oppose environmental policies. Interestingly, the members of this class are not necessarily for suburban lifestyles, but they clearly put more than practical value on the personal motorized travel mode. Note that they are affluent, even more so than the members of the next class, *middle-class homeowners*, but do not own homes as often. Thus, those belonging to this class have (more) economic resources, while they are not highly supportive of the environment. With these unique profiles, the affluent, highly-educated are likely to be affected by built environment-related land use planning and policies more than the members of the other two classes, whose preferences are in many cases in agreement with the residential types they live in.

The ***middle-class homeowner*** class: This class is the smallest, consisting of the remaining 15% of the sample. About 27% of the class are millennials, and about 14% live in either central city or urban neighborhoods. Compared to those of the other classes, more members of this class belong to racial/ethnic minority groups, have some years of college education but are not likely to have a graduate degree, live with a child from 6 to 17, which may affect their location choice, and are in the middle income bracket between $60,000 and $120,000 a year. Their homeownership rate is quite impressive given the high costs of housing in California: the highest among the three classes, 89%. This seems to explain why many more members of this class live in suburban or exurban neighborhoods (50% and 25%), where houses are more affordable to middle-income households than they are in large cities on average. The middle-class homeowners present strong preferences for suburban lifestyles, but somewhat unexpectedly they agree with the idea of “cars as a tool” more than those in the other classes. Although not intuitive at first glance, I can imagine that those in this class are satisfied with cars that fit their needs (e.g., minivans) but are not necessarily equipped with the latest technologies or expressive of self-identity. For example, the middle-class homeowners may have complex travel demands by their household members throughout a day (e.g., pickups/drop-offs of their child at school) under budget constraints and with less than one vehicle per driver. Thus, the connection between perceptions toward cars, the decision to own or share, and the intensity of use may be context-dependent, which many studies in the millennial literature have not explored much.

5.2.2 Choice Model

The latent-class choice model estimates *class-specific* conditional logit models (Table 19). I use three sets of neighborhood-specific variables: neighborhood demographics, economics, and the built environment attributes. Below, while interpreting results, I focus on variables whose influences are more pronounced in each class-specific model. Then, I make connections between the representative individual/household characteristics of each class and the selected set of neighborhood attributes that most strongly influence utility for the members of each class.

The members of the ***younger, pro-urban*** class favor Census block groups having higher shares of older millennials (those between 25 and 34 in 2015). This suggests millennials tend to congregate in neighborhoods that are inhabited by peers with similar tastes, with the share of millennials capturing any remaining effects of neighborhood attributes that are appealing to millennials but are not already captured by the other variables in the model. For example, it may capture (1) those unobserved attributes that were there from the beginning (e.g., historic buildings or a walkable street with locally owned shops/stores) or (2) attributes newly produced/generated because of the increasing presence of millennials (e.g., the sense of community with relatively homogeneous peers or new businesses targeted for the growing customer base of millennials). Unexpectedly, the coefficient of the rental affordability index, the ratio of 12 times the median monthly rent to one's annual income, is not statistically significant. Our interpretation is that this factor is not central to the residential choice of millennials, as the members of this class, most of whom are renters, do not have many options for affordable rental communities, especially when they look for viable urban neighborhoods.

The members of the younger, pro-urban class apparently derive *disutility* from neighborhoods in good school districts. However, this may not be their conscious choice, but rather a byproduct of their strong preferences for viable urban neighborhoods with mixed land-use patterns and consumption amenities (e.g., restaurants, cafes, and bars within walking distance). In other words, the younger, pro-urban class seeks urban neighborhoods, which may happen to be in less well-performing school districts in large cities. Given that many members of this class do not live with school-aged child(ren), they may not (yet) consider school quality as much as those in the other classes.

The members of the ***affluent, highly educated*** class choose their residential locations in ways that are more economics-oriented. For example, they consider the affordability of neighborhoods for renting and buying a house; however, members of this class own homes *less* than those in the last class, *middle-class homeowners*, whose homeownership rate is about 90% and whose members have tighter budget constraints. Moreover, this class derives utility from neighborhoods with higher median incomes, possibly suggesting preferences for well-maintained neighborhoods whose residents have high socioeconomic status. After all, they attach to a car more value than just its practical use: *e.g.*, they view it as a means for the expression of self-identity or by which to pursue materialistic lives. If they do have symbolic values or affections for a car, their seeking for high socioeconomic status appears to be consistent. Interestingly, even though many members of this class live with a school-aged child (6 to 12), they do not appear to look for good school districts as much as those in the next class. Note that 42% of them make more than $120,000 a year, and 90% of them are full-time workers. They certainly seem able to afford to live (and buy a home) in good school districts, but they choose lifestyles instead: *e.g.*, renting or buying homes in cities. After all, they do present preferences for urban lifestyles, although to a lesser extent than the younger, pro-urban class.

Table 19. Class-Specific Choice Models (weighted, n=729)

Attributes (unit: the Census block groups)	Younger, pro-urban (53%)	Affluent, highly educated (32%)	Middle-class homeowners (15%)	Wald test for equality of coefficients
% Non-Hispanic White for a non-Hispanic White commuter	0.02***	0.01	-0.02	10.14***
% Non-Hispanic Asian for a non-Hispanic Asian commuter	0.02**	0.08***	0.17***	16.19***
% Hispanic for a Hispanic commuter	0.01	-0.05***	0.09***	73.97***
% older millennials, age 25-34	0.05***	0.00	0.01	16.72***
Natural log of the median household income (standardized)	-0.01	0.61***	1.44***	33.81***
(median home value) / (annual household income for owners)	-0.03	-0.17***	-0.67***	27.63***
(median rent*12) / (annual household income for renters)	0.04	-1.32***	-1.14	8.72**
Quality of the elementary school (1-10)	-0.05*	0.04	0.43***	21.11***
Natural log of the distance to the workplace/school	-1.47***	-1.53***	-1.52***	0.20
Amenities (factor score)	0.14**	-0.07	-0.85***	17.64***
Land use mix (factor score)	0.31***	-0.06	0.46***	14.21***
Density (factor score)	-0.31***	-0.50***	-0.87***	6.17**
Region				
Central Valley	3.26	-0.40	-2.00	18.28*
MTC	2.83	-8.87	-4.27	
Northern California and Others	3.00	-7.36	-0.87	
SACOG	2.92	-3.59	-3.46	
SANDAG	-5.98	15.06	5.86	
SCAG	-6.03	5.16	4.74	
Reduction in errors compared to the errors of the constant-only model)[1]	0.2656	0.3206	0.5263	
Reduction in errors compared to the errors of the equally likely model)[1]	0.2661	0.3220	0.5273	

* Statistically significant at the 90% level, ** at the 95% level, and *** at the 99% level

[1] As a goodness-of-fit measure, Latent GOLD Choice 5.1 computes the extent to which included covariates reduce the squared prediction errors as a proportion of the squared errors of a baseline model. $R^2 = \frac{Error(baseline) - Error(model)}{Error(baseline)}$, $Error(model) = \sum_{q=1}^{Q} \frac{\sum_{i=1}^{N} \omega_i \cdot \hat{P}(q|\mathbf{z}_i) \cdot \sum_{j=1}^{J} [I_j(y_i) - \hat{P}(j|\mathbf{x}_{ij}, q)]^2}{\sum_{i=1}^{N} \omega_i \cdot \hat{P}(q|\mathbf{z}_i)}$, $Error(constant\ only) = \sum_{q=1}^{Q} \frac{\sum_{i=1}^{N} \omega_i \cdot \hat{P}(q|\mathbf{z}_i) \cdot \sum_{j=1}^{J} [I_j(y_i) - (Market\ share\ of\ j\ in\ class\ q)]^2}{\sum_{i=1}^{N} \omega_i \cdot \hat{P}(q|\mathbf{z}_i)}$, and $Error(equally\ likely) = \sum_{q=1}^{Q} \frac{\sum_{i=1}^{N} \omega_i \cdot \sum_{j=1}^{J} [I_j(y_i) - \frac{1}{J}]^2}{\sum_{i=1}^{N} \omega_i}$, where q denotes a latent class, i $(1, 2, \ldots, N)$ an individual case, ω_i the weight of individual i, $\mathbf{z}_i$ covariates in the membership model, j $(1, 2, \ldots, J)$ alternative j in the choice model, y_i the index of i's chosen alternative $(1, 2, \ldots, J)$, $I_j(y_i) = 1$ if individual i chooses alternative j and otherwise 0, and $\mathbf{x}_{ij}$ the attributes of alternative j for individual i (Vermunt & Magidson, 2016). Note that in this study, the ten unlabeled alternatives in the choice set are randomly sorted, so the amounts of reduced errors against these two baseline models do not differ much.

Table 20. The Differences between the Chosen Alternative and Those in the Choice Set (n=729, weighted)

Class	Choice set (means)			Chosen alternative			Differences		
	Younger, pro-urban	Affluent, highly educated	Middle-income homeowners	Younger, pro-urban	Affluent, highly educated	Middle-income homeowners	Younger, pro-urban	Affluent, highly educated	Middle-income homeowners
	(1)	(2)	(3)	(4)	(5)	(6)	= (4) - (1)	= (5) - (2)	= (6) - (3)
Neighborhood demographics									
% NHW for NHW cases	17.236	20.941	10.093	21.658	26.443	11.096	4.422	5.502	1.003
% NH-Asian for NH-Asian cases	3.507	1.741	1.642	4.010	3.611	4.929	0.503	1.870	3.287
% Hispanic for Hispanic cases	13.834	11.655	20.444	15.050	5.721	31.602	1.216	-5.934	11.158
% older millennials (25-34)	14.912	15.392	14.480	18.421	14.913	14.749	3.509	-0.479	0.269
Neighborhood economics									
ln(median household income) [1)]	-0.111	-0.057	-0.098	-0.186	0.371	0.041	-0.075	0.428	0.139
Ratio of median home value to annual income	1.942	2.526	7.083	1.821	2.867	5.285	-0.121	0.341	-1.798
Ratio of median rent to annual income	0.551	0.170	0.066	0.483	0.141	0.036	-0.068	-0.029	-0.030
Elementary school rate	5.497	5.525	5.573	5.345	6.415	5.796	-0.152	0.890	0.223
Built environment attributes									
ln(commute distance)	2.718	2.839	2.922	1.859	2.222	2.305	-0.859	-0.617	-0.617
Amenities	0.207	0.225	0.092	0.623	0.259	-0.354	0.416	0.034	-0.446
Land use mix	0.005	-0.028	0.022	0.324	0.074	0.169	0.319	0.102	0.147
Density	0.216	0.230	0.175	0.189	0.031	-0.031	-0.027	-0.199	-0.206

1) Standardized.

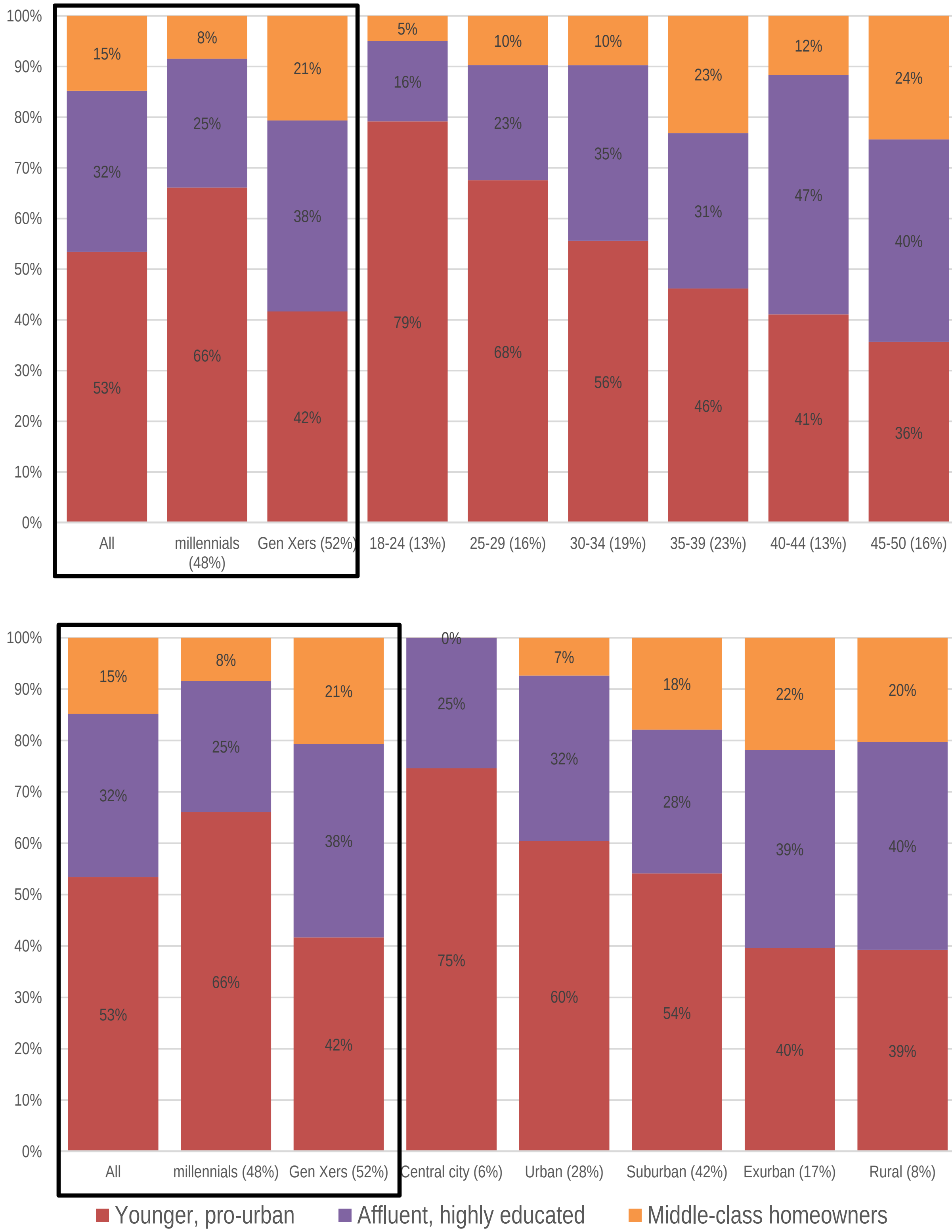
The ***middle-income homeowner*** class derives utility by choosing neighborhoods with higher median income (a proxy for the socioeconomic status of neighborhoods) and neighborhoods whose home values are more affordable to them. Not surprisingly, the middle-class homeowner class is the only class that derives utility by living in good school districts. After all, on average the members of this class live with the highest number of children from 13 to 17 among the classes. They appear to accept traditional family-oriented suburban lifestyles by seeking land use mix (i.e., neither neighborhoods in or close to the central city nor exclusively residential neighborhoods in suburbs), but not for urban amenities or density.

5.2.3 Distribution of Latent Classes by Age and Neighborhood Type

Figure 7 presents the shares of the three latent classes by age and chosen residential neighborhood type. At the aggregate level, millennials and Gen Xers appear to differ primarily in their proportions of the first two classes, younger, pro-urban and affluent, highly-educated. While 25% of millennials belong to the latter, 38% of Gen Xers do so. In comparison, while 66% of millennials prefer urban lifestyles, only 25% of Gen Xers do so. If I compare the difference within and across the two generations at a more disaggregate level, more variations start to emerge. For example, among those under 25, an estimated 79% belong to the younger, pro-urban class and 16% to the affluent, highly-educated. In contrast, among those older than 44, 36% belong to the younger, pro-urban class and 40% to the affluent, highly-educated class. I see other patterns in the share of the three latent classes by the chosen neighborhood type. For instance, 75% of those living in central city neighborhoods are younger, pro-urban members, whereas only 40% of those in exurban or rural neighborhoods are. In contrast, the middle-income homeowner class, whose members value affordability, school quality, and job-housing balance, can be found in sizable shares among those living in suburban, exurban, and rural neighborhoods, but not those in central city or urban neighborhoods, where housing is expensive and public schools are not as competitive.

At least two observations from Figure 7 are worth mentioning. First, popular notions or claims about millennials in the media are often biased in part because researchers and journalists choose to observe certain segments of millennials (e.g., those young adults in central cities or in their 20s), but not the entire group of millennials. In this context, this dissertation provides a comprehensive picture of young and older adults in terms of their heterogeneous residential preferences. Second, I see decreasing shares of the younger, pro-urban class and increasing shares of the affluent, highly-educated and middle-class homeowner classes as age increases. Note that these bar charts are drawn on a cross-sectional dataset collected in fall 2015, so I do not know for sure whether 25 to 29-year-old millennials in the chart will behave in the same way as that of 30-34-year-old millennials in the chart five years later (i.e., in 2020). Still, I may well expect to see trends in this direction to take place in coming years. Thus, planners and policymakers need to be aware of unique demands by the members of different latent classes for housing, neighborhoods, and transportation infrastructures.

Figure 7. The Share of Latent Classes by Age and Neighborhood Type (weighted, n=729)



5.2.4 *Implications for Commute Patterns*

After revealing the distinctive set of neighborhood attributes that the members of each latent class seek, I explore the pairs of residential and work/study neighborhood types for the three latent classes. That is, *given* the neighborhood type of one's workplace/school, I want to examine which residential neighborhood type the members of each class choose. Note that in this dissertation, I assume that work/study locations are exogenously given to commuters, which, previous studies find, may not always hold true (Waddell, Bhat, Eluru, Wang, & Pendyala, 2007a). Whether the three classes present unique patterns of home-work/study pairs, which differ from class to class, is the main question here. If commuters in the sample transition from one class to another in response to changes in socioeconomic/demographic characteristics and attitudes in coming years, the analysis of the patterns of home-work/study pairs helps planners and policymakers predict where I may see changes in demand for housing and neighborhoods and supports them in preparing plans and policies with a deeper and more nuanced understanding of location choice behavior.

Table 7 presents the distinctive patterns of home and work/study neighborhood types, which vary from one latent class to another. The four tables on the left include the percent of commuters who choose to live in five neighborhood types *given* a neighborhood type of their workplace/ school. In these tables, the columns refer to residential neighborhood types and the rows, workplace/school neighborhood types. For example, the first row in Table 7-(A) shows that among those who commute to central city neighborhoods, 33% choose to live in central city neighborhoods, while 23% choose the suburbs. The far right column in Table 7-(A), All residence, indicates the percent of those who *commute* to a certain neighborhood type in each class, while the bottom row, All work/school, presents the percent of those who choose to *live* in a certain neighborhood type in each class. The fourth table on the left, Table 7-(D) All, presents the average percent for the sample (weighed, n=729). The first three tables on the right display the difference in percentage points between each of the three class-specific Tables 7-(A), (B), and (C) and the bottom table, 7-(D). These three tables clarify how much each cell in the three class-specific tables *deviate* from the same kind of values in the average table.

In Tables 7-(E) through 7- (G), three latent classes present the unique patterns of home and workplace/school pairs in terms of neighborhood types. In Table 7-(G), Middle-income homeowners tend to live in suburban neighborhoods, whose houses are more affordable than those in cities. Many members of the Younger, pro-urban class are found to live in neighborhoods that are denser than those that they commute to: in 7-(E), many cells under the diagonal line from the top left to the bottom right are blue-coded, while cells on the other side are red-coded. Moreover, many members of this class choose either central city or urban neighborhoods. As expected, many members of the Affluent, highly-educated class find their homes in neighborhoods that are less dense than those that they commute to: in 7-(F), many cells above the same diagonal line are blue-coded.

The model can be used to investigate what might happen if members of the Younger, pro-urban class were to metamorphose into members of the Middle-class homeowners class over time. Table 7-(H) presents the outcome of such a scenario, the values of which are the percentage point differences between those in Tables 7-(E) and 7-(G). It suggests that they will relocate

Table 21. The Shares of Residential Neighborhood Types (columns) *given* Work/School Neighborhood Types (rows) (weighted)

(A) Younger, pro-urban

(53%)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	33%	37%	23%	1%	5%	10%
Urban	13%	59%	23%	3%	1%	27%
Suburban	3%	25%	55%	12%	6%	44%
Exurban	0%	6%	47%	34%	13%	13%
Rural	0%	0%	55%	30%	15%	6%
All work/school	8%	32%	42%	12%	6%	100%

(E) Younger, pro-urban (the %point difference from the mean)

= (A) - (D)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	3%	3%	-3%	-2%	-1%	2%
Urban	3%	6%	-5%	-3%	-1%	0%
Suburban	1%	2%	3%	-4%	-2%	1%
Exurban	0%	1%	6%	-6%	-1%	-1%
Rural	0%	0%	6%	2%	-8%	-1%
All work/school	2%	4%	1%	-4%	-2%	0%

(B) Affluent, highly educated

(32%)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	33%	26%	21%	9%	10%	6%
Urban	8%	58%	26%	5%	3%	29%
Suburban	0%	21%	47%	23%	9%	43%
Exurban	0%	6%	35%	47%	11%	14%
Rural	0%	0%	36%	24%	40%	8%
All work/school	5%	28%	37%	20%	10%	100%

(F) Affluent, highly educated (the %point difference from the mean)

= (B) - (D)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	3%	-9%	-4%	6%	4%	-1%
Urban	-1%	4%	-3%	-1%	1%	1%
Suburban	-1%	-1%	-5%	7%	1%	0%
Exurban	0%	1%	-6%	7%	-2%	0%
Rural	0%	0%	-13%	-4%	18%	1%
All work/school	-1%	0%	-5%	4%	2%	0%

(C) Middle-class homeowners

(15%)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	0%	39%	59%	2%	0%	5%
Urban	0%	19%	54%	22%	5%	25%
Suburban	0%	17%	51%	18%	14%	42%
Exurban	0%	0%	36%	46%	19%	19%
Rural	0%	0%	60%	31%	9%	10%
All work/school	0%	14%	50%	25%	11%	100%

(G) Middle-class homeowners (the %point difference from the mean)

= (C) - (D)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	-30%	4%	34%	-2%	-6%	-3%
Urban	-10%	-34%	26%	16%	2%	-2%
Suburban	-2%	-6%	0%	2%	6%	-2%
Exurban	0%	-5%	-6%	5%	5%	5%
Rural	0%	0%	10%	3%	-14%	2%
All work/school	-6%	-14%	9%	8%	3%	0%

(D) All

(100%)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	30%	34%	26%	3%	6%	8%
Urban	10%	53%	28%	6%	2%	27%
Suburban	2%	23%	52%	16%	8%	43%
Exurban	0%	5%	41%	40%	14%	14%
Rural	0%	0%	49%	28%	23%	7%
All work/school	6%	28%	42%	17%	8%	100%

(H) Scenario: Younger, pro-urban -> Middle-class homeowners

= (G) - (E)	Central city	Urban	Suburban	Exurban	Rural	All residence
Central city	-33%	1%	37%	1%	-5%	-5%
Urban	-13%	-40%	31%	19%	4%	-2%
Suburban	-3%	-8%	-3%	6%	8%	-2%
Exurban	0%	-6%	-11%	12%	6%	6%
Rural	0%	0%	5%	1%	-6%	3%
All work/school	-8%	-18%	8%	12%	5%	0%

1. In the left tables, the cell values represent the shares of commuters from five types of residential neighborhoods (columns), given a work/school neighborhood type (rows). For example, in Table (A), the first five cells in each row

sum to 100%, those who work at one of the five neighborhood types (rows) and belong to the *Younger, pro-urban* latent class. In the left tables, the yellow bar indicates the size of the percent in each cell.

2. In Tables 7-(E) through 7-(G), the blue bars show the increase in percentage points of a cell in a latent class, compared to the same positioned cell in the mean table, Table (D). Similarly, the red bars show the decrease in percentage points of a cell in a latent class compared to the same positioned cell in the mean table, Table (D). The cells in Table 7-(H) present the difference in percentage points between those in Table 7-(G) and Table 7-(E), under the assumption that all members of the Younger, pro-urban class will switch to the Middle-class homeowners class and change their commute patterns as a result. Here, red cells indicate losing shares, and blue cells indicate gaining shares.

away from the dense part of metropolitan areas, which may cause longer commutes, more dependence on personal vehicles, or more congestion during peak hours.

5.3 Discussion

This dissertation finds LCCM to be an effective analytical tool for the identification of taste heterogeneity in the residential location choice context. Its choice model helps explore the presence, share, and forms of heterogeneous preferences, and its membership model helps understand the socioeconomic, demographic, and attitudinal profiles of individuals belonging to the classes with such heterogeneous preferences. Using LCCM, this dissertation finds, first, that not all millennials conform to their urban stereotype, and not all urban residents present preferences for rich urban amenities. In other words, residential preferences are neither defined by arbitrary age thresholds nor by the actual choice: instead, LCCM probabilistically assigns individuals to classes with distinctive preferences by employing their personal traits and choice settings, which produces a rich and nuanced understanding of choice behavior of millennials and Gen Xers. In this sense, whether or not millennials *as a whole* behave differently compared to older birth cohorts may not be the right question. Instead, we need to examine how many urban-/suburban-oriented millennials I have in a certain area/region. Nationwide statistics at aggregate levels (e.g., migration rates/counts between central cities and suburban counties) may not provide useful insights/guidance for specific local contexts. Thus, I suggest that planners analyze local data with a latent class approach and thereby be informed of the extent to which their communities may encounter an undersupply of certain types of housing units, or a mismatch between existing stocks and emerging demands.

Second, this dissertation finds a group consisting of *both* millennials and Gen Xers with strong preferences for urban lifestyles and rich consumption amenities near home. After all, heterogeneous residential preferences are present within and across generations, and not only (many) millennials but also (some) Gen Xers appear to fit the stereotype of today's young adults in popular media. The members of this group view cars as a practical tool for moving around, but not one for the expression of one's social status or self-identity. They also support policies that protect the environment through the regulation of automobile trips, so their dependence on cars for daily travel needs may not be as much as that of the other latent classes, if they have regular access to cars. Interestingly, 40% of this group reside in dense urban neighborhoods, but the remaining 60% do not. Thus, their location choice patterns suggest that suburban communities may see unmet, or latent, demands for urban amenities and more multimodal travel. Note that the choice of urban or suburban neighborhoods is not entirely attributable to preferences of individuals; it is also a response to the availability/affordability of preferred neighborhoods (and housing units) in the local housing market. Thus, the provision of affordable housing in cities, or the further densification of (some) urban neighborhoods, can be effective solutions for the promotion of sustainable developments and transportation.

Third, given that the housing and neighborhood search is inherently constrained by several factors (e.g., the location of one's workplace/school, the affordability of available housing units at the time of search, or intra-household negotiation and compromises), it will be a fruitful stream of research to explore differences between individuals with successful and less successful searches: i.e., consonant versus dissonant residents. The travel behavior literature has demonstrated that these two groups of residents differ in travel behaviors, mobility choices, or travel satisfaction; however, the way that researchers measure the degree to which individuals undergo consonance/dissonance between residential preferences and the attributes of their chosen neighborhoods has not been thoroughly examined and innovative solutions have not been extensively searched for. In this context, researchers may want to define consonant/dissonant residents in less-explored ways: e.g., the members of the younger, pro-urban class who live in sprawled suburban neighborhoods (i.e., dissonant residents) and other members of the same class who live in the central city or urban neighborhoods (i.e., consonant residents). Instead of self-reported residential preferences (i.e., responses to Likert-scale statements in surveys), the use of revealed preferences through the actual choice of a residential neighborhood (e.g., a posterior class membership or the probabilities of belonging to latent classes) may provide fresh insights on the way consonant/dissonant residents respond to the built environment and transportation infrastructure. This approach will shed light on actual effects of a neighborhood/city/region failing to meet the preferences of their residents and help prepare policy and incentives that improve the match between supply of and demand for various types of neighborhoods.

There are some limitations to the dataset and analytical approaches used in this study. First, since I analyze a cross-sectional data set collected in the fall of 2015, I do not claim that today's young adults will behave tomorrow in the same ways as today's older adults. To overcome this limitation, a second-wave survey is being administered in the summer of 2018, which will become a part of multi-wave rotating panel for this project. Second, missing variables in the models may affect location choice in non-trivial ways. For instance, regarding individual characteristics, their financial situations (e.g., the amount of debt from student loans) may account for their choice of renting versus buying a home. Regarding neighborhood attributes, crime rates may reveal additional preference heterogeneity. Also, land use variables are borrowed from the EPA Smart Location Database, which is becoming outdated since its last update in July 2013. Third, the questions of whether and to what extent individuals actively choose versus inevitably accept housing and neighborhoods that are available in the market lie beyond the scope of this study; however, they are of the utmost importance to academics, planners, and policymakers. The answers to these questions will certainly vary by region. Thus, the forms and shares of heterogeneous residential preferences found in this dissertation need to be understood as specific to California, which has been notorious for insufficient affordable housing.

CHAPTER 6. HOW SHOULD PLANNERS AND POLICYMAKERS RESPOND?

6.1 Why are the Current Literature Gaps so Critical?

The literature review section (Chapter 2) identified several gaps in the literature on the travel behavior and location choice of millennials. Related to these gaps, this section suggests a framework that illustrates why these gaps matter and what planners and policymakers can do to better meet the demand of today's young adults and their successors in the coming years (Dimock, 2018). The research undertaken for this dissertation is reflected in the schematic presented in Table 22, which indicates that millennials are heterogeneous in their travel behavior and location choices. The table lists four types of millennials based on the primary factors underlying their current behavior and choices. In this framework, millennials belong to one of two groups for each of the two dimensions, travel behavior and location choice. That is, the choice or behavior of one group is better explained by attitudes and preferences (e.g., pro-urban lifestyles or active modes) and that of the other group is better understood by their economic situations and life course events (e.g., student/worker status, household income, or the presence of children in their household).

Since studies in the literature have generally used travel behavior and location choice to categorize millennials, Table 22 identifies four distinctive groups. Each cell in the table presents a scenario that predicts how members in the cell will behave in the near future: (1) either stay in cities or move to the suburbs or (2) either travel mostly by cars or depend less on cars. Note that for simplicity, the table presents these four groups as if attitudes toward one dimension (e.g., travel modes) are independent from those toward the other dimension (e.g., built-environment attributes). In addition, the descriptions of the scenarios listed in table compare the expected behavior and choice of these distinctive groups of millennials to the typical behavior and choice of preceding generations when they transitioned to more mature adulthood, for example, when they were between 35 and 44 years old.

Table 22. Expected future choice/behavior by four types of millennials

	RC (**BE**) by attitudes/preferences	RC (**BE**) by economic factors
TB by economic factors	Scenario 1: Urban lifestyles, but with cars • **BE**: relocating to relatively more compact neighborhoods • **TB**: driving less, but traveling more by alternative modes (because of BE)	Scenario 2: Catching up later • **BE**: relocating to similar neighborhoods (e.g., auto-oriented sprawling suburbs) • **TB**: traveling similarly to those who are 35-44 today
TB by attitudes/ preferences	Scenario 3: Urbanites most of their lives • **BE**: relocating to relatively more compact neighborhoods • **TB**: driving far less, but traveling far more by alternative modes (because of BE + AT)	Scenario 4: Suburbanites, but cars merely a tool • **BE**: relocating to similar neighborhoods (e.g., auto-oriented sprawling suburbs) • **TB**: driving less, but traveling more by alternative modes (because of AT)

Notes: TB stands for travel behavior, RC residential (location) choice, and BE the built environment. These acronyms come from Cao, Mokhtarian, and Handy (2009)

We expect some millennials to behave differently from others as long as local housing markets and available transport infrastructures allow them to make choices based on their attitudes or economic situations. While the popular media concentrate on scenarios 2 and 3, we will also likely have two additional groups in scenarios 1 and 4 that constitute varying shares of the millennial population. As their relative shares are less clear, this raises the following questions: Which group will dominate as millennials age? And what will their shares be? If we ignore possible heterogeneity within millennials and instead focus on their "sample-average" coefficients, we are likely to be misled.

Figure 8 presents four hypothetical examples of the distributions of millennials based on the two dimensions. For each of the examples, it also maps sample-average coefficients derived from OLS estimation. Note that the distributions assume, for the sake of simplicity, that the standard deviation in one dimension is identical to that in another dimension. From the hypothetical distributions presented in Figure 8, planners and policymakers would likely require some additional information such as (1) which quadrant contains the majority of millennials and (2) how large the shares of millennials in the other three quadrants are. The answers to these questions are critical to investment decisions related to land-use regulations and transportation infrastructure. Without such knowledge of millennial behavior, planners and policymakers could either (1) lose an opportunity presented by a nontrivial segment in the population whose members are willing to retain sustainable behavior and choice if circumstances are favorable, or (2) develop biases against young adults who may not find urban lifestyles or non-motorized travel modes preferable, resulting in unsatisfactory outcomes (K. Ralph & Delbosc, 2017). For example, if the scenario depicted Figure 8-(B) is the case, planners and policymakers may make serious mistakes if they assume that all millennials are lifetime urbanites. As another example, if Figure 8-(C) presents an accurate distribution of the millennial population, planners and policymakers may fail if they design policies and incentives that target only those millennials who will behave as their parents did at the same age (i.e., buying home in the suburbs and traveling mostly by cars). In these two cases, while one segment is highly satisfied, the others are not. In either case, ill-informed decisions can result in the ineffective use of limited resources and the loss of opportunities for sustainable development.

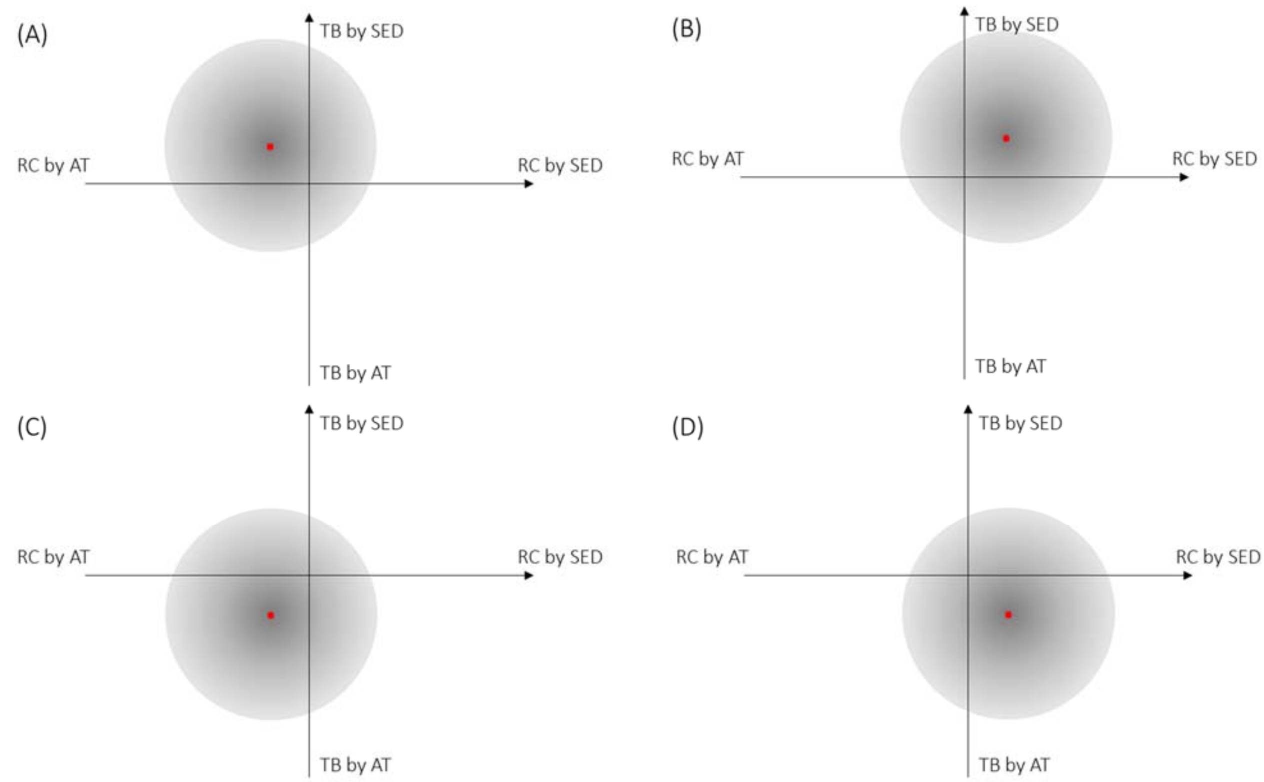


Figure 8. Hypothetical distributions of millennials defined in Table 22

Notes: The gradual change in tone inside each circle indicates the varying density of millennials by location in the circle. The red dots present the sample-average coefficient under each scenario.

If, indeed, millennials are a heterogeneous group, as this dissertation finds, the dynamic nature of attitude formation requires urgent action. Existing studies suggest that attitudes are not fixed qualities but prone to longitudinal changes in response to various factors. Such changes may be expressed *voluntarily* or *involuntarily*. The former includes cases in which a young adult starts a family, raises a child, and changes attitudes towards travel modes and the built environment. These cases would be considered voluntary since external factors, including availability/quality of travel modes and access to various places from home, do not induce these young adults to adjust their behavior. The latter, which includes cases in which changes in attitude occur in response to interactions with external factors, are considered involuntary. For example, Chatman (2009) suggested a process in which individuals may change their residential preferences after relocating to a neighborhood whose attributes are not consistent with their preferences. That is, these individuals would reduce their "cognitive dissonance" between preferences and actual choice by adjusting their preferences to be more aligned with their choices (Festinger, 1962). Of course, these changes are a natural process many individuals go through after relocating because they compromise and make tradeoffs between competing search criteria such as good school districts versus stores and restaurants within walking distance from home. Although these cases represent *involuntary* changes in attitudes, this dissertation is less concerned about these individuals because they make informed decisions under "their own" competing interests.

Another *involuntary* case that requires more attention from planners and policymakers is one in which individuals *do* prioritize neighborhoods that support their lifestyles but cannot find them because such options are lacking in their region. Therefore, these individuals are more likely to choose neighborhoods that are not consistent with their attitudes toward preferred travel modes and surrounding development patterns. Few researchers have empirically tested the ways individuals adjust their attitudes and preferences after relocating over a long time period if their ideal choices are not available (i.e., the region lacks options that support the attitudes of these individuals) (Schwanen & Mokhtarian, 2005). Some may adjust their attitudes after relocating (e.g., by reducing cognitive dissonance), others may keep the same attitudes as before, but are less satisfied with everyday trips and neighborhoods, and still others may, over time, gain additional information and relocate to other regions that provide more preferable options. In these three scenarios, the subgroup of the population who support sustainable transportation and development and are able to live and travel accordingly would decline.

The availability of affordable units is critical for the success of plans that promote sustainable development. Therefore, planners and policymakers should include housing as an important component of plans that accommodate the attitudes and preferences of millennials. Studies find that overly restrictive land-use regulations such as those related to density, allowable land use, and minimum lot size tend to increase housing costs and accommodate only a select group of residents in such urban neighborhoods (Ganong & Shoag, 2017; Glaeser & Ward, 2009; Lens & Monkkonen, 2016). Given that millennials have undergone unfavorable economic conditions such as the Great Recession of 2007-2009 and increasing debt from student loans, they may find it difficult to move to or stay in amenity-rich urban neighborhoods that support walking, biking, and riding public transit. Note that exposure to such built environments while the values, beliefs, and attitudes of young adults (e.g., in their 20s) are still forming may have *a greater influence* on their travel demand later in the life (Smart & Klein). Thus, developing plans that accommodate the unique demand of young adults is critical to promote sustainable travel behavior over the long term.

6.2 Key Findings of the Latent-Class Location Choice Model

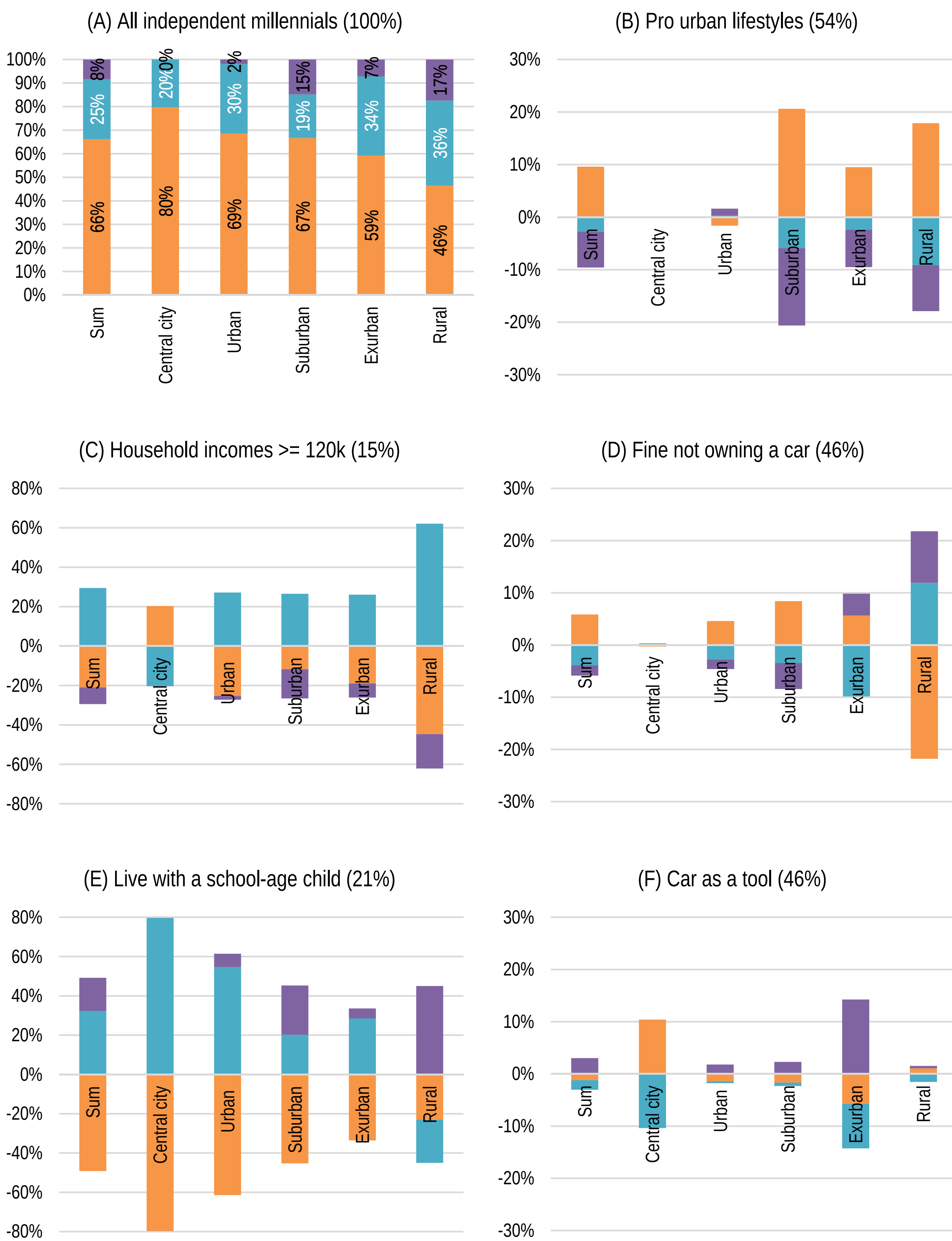
This section presents key findings from the latent class location choice model introduced in the previous chapter and discusses future location choices of millennials in the analysis. Table 23 displays six bar charts. Chart (A) shows the shares of three latent classes by five neighborhood types for the millennials included in the analysis. The other five charts, (B) through (F), present *differences in percentage points* between the aforementioned shares and those for millennials in certain subgroups. That is, in Charts (B) through (F), the bars above zero indicate a larger share for a given subgroup that that for all millennial cases in the analysis, and vice versa. Charts (C) and (E) present the shares for certain economic and demographic subgroups, and Charts (B), (D), and (F) present the shares of subgroups with factor scores greater than zero (i.e., cases with larger factor scores than the original sample mean (n=1,975)).

The shares of the three latent classes by neighborhood type change more by economic and demographic covariates than by attitudinal factors. For those in the high-income bracket in Chart (C), their shares of the Affluent highly educated class are larger in most neighborhood types compared to those for all millennials in the analysis. Their larger shares are pronounced in suburban, exurban, and rural neighborhoods, suggesting that many members of this class find neighborhoods with large houses. For those who live with school-age children (between 6 and 17), their shares of the Affluent highly educated class are larger in most neighborhood types including central city and urban neighborhoods. This pattern makes sense because only affluent families are able to afford to live and raise children in the dense part of a region. In comparison, for millennials with school-age children who live in suburban and rural neighborhoods, the Middle-class homeowner class constitutes larger shares, in part, because of more houses becoming affordable to the middle income. Interestingly, in all neighborhood types, the Young pro-urban class comprises smaller shares of millennials with children than all millennials in the analysis. In brief, Charts (C) and (E) suggest that today's young adults may switch their class membership from Young pro-urban to Affluent highly educated when they earn higher incomes and raise their children in the future.

In Chart (B), millennials with stronger pro-urban lifestyles are *not* necessarily *more* present in dense mixed-use transit-rich urban neighborhoods. Many of these millennials are in the Young, pro-urban class, but live in suburban, exurban, or rural neighborhoods with schools/workplaces located far from the central city. Thus, even though they may value neighborhoods with rich consumption amenities and mixed use development patterns (i.e., which are more common in urban neighborhoods), their *realistic* alternatives (e.g., constrained by commuting distances) are found more in the suburbs, exurbs, or rural areas, suggesting *latent* demands of suburban young adults for neighborhoods with rich consumption amenities. In the meantime, Charts (D) and (F) show greater shares of millennials with flexible attitudes towards car ownership and driving in central city or urban neighborhoods. Thus, even if millennials undergo once-postponed life course events, some of those with *less* affection for cars will choose urban neighborhoods in which alternative modes are viable so that they can follow their preferred means of travel, at least for some of their daily demands.

In sum, the charts in Table 23 shed light on the heterogeneous residential preferences of millennials and identify a plausible trajectory of their future location choices. Given the limited generalizability (e.g., a cross-sectional analysis) of these findings, researchers are advised to examine their own regions to provide effective policy suggestions for local planners and policymakers.

Table 23. The share of three latent classes with heterogeneous residential preferences



Notes: In each chart, orange indicates Young pro-urban, blue Affluent highly-educated, and purple Middle-class homeowners. The share of each subgroup within the millennial population in the analysis is shown inside the parentheses of the chart titles. Note that the y axis ranges from zero to 100 percent in Chart (A), from -80 to +80 *percentage point* differences in Charts (C) and (E), and from -30 to +30 *percentage point* differences in Charts (B), (D), and (F).

6.3 Suggestions for Future Research

6.3.1 Individual-level Panel with Attitudes and Life Course Events

Identification of latent groups with heterogeneous preferences within the millennial population of a region is critical for estimating the future choices of each subgroup in this population. Unfortunately, while advanced analytical approaches for the estimation of such groups have been developed, appropriate data are not widely available. A latent class analysis (either clustering or choice) that helps planners and policymakers respond to local demands requires several key categories of information: (1) the basic socioeconomic and demographic characteristics of individuals and households; (2) attitudes, *at least* on travel modes and the built environment (but ideally on more dimensions); (3) recent life course events; (4) residential and commute locations that are accurate down to the x-y geocode level; and (5) the measures of travel behavior (e.g., frequencies by purpose and mode in a typical week).

Conventional trip-diary surveys such as the National Household Travel Survey (NHTS) provide detailed information for planners and policymakers in categories (1) and (5), and limited information in category (4) at aggregate levels such as the census tract or the traffic analysis zone, but usually not categories (2) and (3). However, in many cases, attitudes and recent life course events may clarify the reasons underlying the behaviors and choices of individuals. In other words, although socioeconomic and demographic characteristics provide an understanding of the average responses of various socioeconomic groups, they do not always explain the reasons behind those responses. Attitudes and recent life course events are more relevant to studies about millennials because they reportedly differ in attitudes from older cohorts and their recent/near-future life course events transform the way that they choose residential locations and make trips. Without these covariates, models predicting the future housing and travel demand of millennials suffer from omitted variable bias, which produce biased estimates that fail to correctly inform planners and policymakers.

Since young adults in any cohorts undergo *dynamic* processes in which attitudes, choices, and behaviors interact with and affect one another, we need dynamic models that account for outcomes at a *later* point in time (e.g., residential choice, travel behavior, and even attitudes) by individual and household characteristics, built environment attributes, and behaviors and choices at a previous point in time, and any exogenous changes in these covariates between the two points. The ideal form of input data, in other words, is panel data, which follow the same individuals over time. Transportation researchers have long emphasized the merits of individual-level panel data (Mokhtarian & Cao, 2008; Ortúzar, Armoogum, Madre, & Potier, 2011), and a few have had the privilege of analyzing panel data to answer less-explored questions with fresh insights (Chen & Chen, 2009; Klein & Smart, 2017; Krizek, 2003; Kroesen, 2014; Kroesen, Handy, & Chorus, 2017; Smart & Klein, 2017). Nevertheless, the transportation planning and travel behavior literature lack panel studies with a focus on millennials. Some have employed repeated cross sections as a pseudo-panel, which helps predict longitudinal changes at an aggregate level (Blumenberg et al., 2016; Deka, 2018b; McDonald, 2015; Vij et al., 2017; Zhong & Lee, 2017). This approach, unfortunately, still suffers from sampling biases that differ from one data collection point to another. In addition, region-specific repeated cross-sectional data are still scarce, so substantive heterogeneity across regions may have not been explored fully.

6.3.2 Interactions of Life Course Events, Attitudes, and Latent Class

One core question that remains unanswered in the millennial literature is how young adults of today will make everyday choices and decisions for medium-term lifestyles *in the coming years*. Related to this question, the mobility biography literature sheds light on the dynamic interactions that young adults will undergo in the near future. Studies in the literature present life course events such as changes in household composition, relocation, and changes in jobs, which affect everyday choices by pressuring individuals to reevaluate "habitual" choices in response to new circumstances (Müggenburg, Busch-Geertsema, & Lanzendorf, 2015; Van Acker, Van Wee, & Witlox, 2010). Unfortunately, many studies in the millennial literature do not incorporate the findings and insights of the mobility biography literature mainly because of the lack of relevant information in conventional travel surveys. Note that most young adults of any cohort (e.g., those in their late 20s or early 30s) undergo transformative life course events for the first time (e.g., starting a job or buying a house) or more frequently (e.g., relocating). Thus, incorporating life course events in conceptual and analytical frameworks is relevant and critical for understanding and forecasting. That being said, most studies, if not all, in the mobility biography literature do not take into account attitudes at the time of the first observation in their panel or changes in attitudes over the following waves of observations. That is, we do not yet understand *the interactions between life course events and attitudes,* which may affect the final choices of individuals (e.g., whether to commute by car or public transit) and the way that these choices are made (e.g., the value of travel time in the mode choice context). In addition, as is the case of static models with cross-sectional data, *the identification of latent classes* with heterogeneous lifestyles and preferences is a key component in dynamic models with panel data. After all, we do not yet know whether individuals stay in the same latent class as they go through life course events. If they switch from one class to another, planners and policymakers may want to understand which factors affect their class membership in which ways so that they can develop effective plans and policies that meet evolving demands for travel and housing while promoting sustainable transportation and development.

Equation (20) is the example of a functional form that accounts for a measure of travel behavior or location choice[3] of individual *i* at time *t*:

$$Y_{it} = \sum_{c=1}^{C} p_{itc|X_{it}} \cdot f\,(E_{i(t-1,\,t)},\, AT_{it-1},\, E_{i(t-1,\,t)} \cdot AT_{it-1},\, X_{it}) \qquad (20)$$

where Y_{it} represents an outcome of interest, with $E_{i(t-1,\,t)}$ life course events between time $t-1$ and t, and AT_{it-1}, attitudes at time $t-1$, $E_{i(t-1,\,t)} \cdot AT_{it-1}$, their interactions, and X_{it}, other controls at time t. Note that Equation (20) also incorporates unobserved heterogeneity within a sample by estimating the probability of individual *i* belonging to class *c* at time *t*, p_{itc}, and multiplying this probability by a certain functional form *f* of the aforementioned explanatory variables over *C* ($c=1, 2, \ldots C$). While Equation (20) assumes that the class

[3] A simple example of Y_{it} is the log-transformed vehicle miles traveled per week by individual i at time t.

membership model accepts only X_{it} as explanatory variables, this limitation is placed here for the sake of simplicity. Also note that class-specific probabilities, p_{itc}, are estimated separately for each wave in the panel above. The nature of repeated observations for the same individuals can be taken into account via individual-specific dummies, robust standard errors, or the estimation of first differences. In addition, Equation (20) excludes AT_t from the right-hand side because it is endogenous to Y_{it} (Kroesen et al., 2017). If we find effective instruments for AT_t (or for $\Delta AT = AT_t - AT_{t-1}$), we can include $\widehat{AT}_t$ and employ a two-stage least squares (2SLS) approach. In sum, the example shown in Equation (20) answers the following set of questions that remain unanswered in the millennial literature but are critical to understanding and forecasting.[4]

1. Do recent life course events affect the present outcome of interest while attitudes are controlled for and if so, to what extent do they do so?
2. Do recent life course events interact with past attitudes, and if so, in what ways?
3. How does the class membership of individuals change from the past to the present?

6.4 Suggestions for Planning Practices

6.4.1 Monitor Regional Trends of Travel Modes and Neighborhood Attributes

6.4.1.1 Add Attitudes and recent life Course Events to Regional Travel Surveys

Regions vary in the shares of millennials with *latent* modality styles and residential preferences. Studies find that metropolitan areas differ by the composition of their labor force (i.e., their labor force highly skilled or less skilled), suggesting that preferences for

[4] A few exceptions include Kroesen (2014) with the five waves of the Dutch mobility panel and Vij et al. (2017) with two repeated cross-sectional datasets for the San Francisco Bay Area in California.

neighborhoods and travel modes differ from one metropolitan area to the next (Ganong & Shoag, 2017; S. Lee, 2010). Thus, planners and policymakers are advised to examine the composition of latent classes in their regions to better serve local demand while promoting sustainable development. One effective way is to conduct regional panel surveys on the choices of residential location and the use of travel modes as well as attitudes and life course events. Such surveys contribute to one's understanding of both current choices/behaviors and the factors affecting them. Compared to cross-sectional surveys administered once per decade, the current practice in many regions, panel surveys are costly. Nevertheless, both rotating panel and repeated cross-sectional surveys with *retrospective* questions actually lead to cost savings and improve the validity of causality claims. Panel surveys help tease out the effects of micro-scale attributes (e.g., education, marriage, childbearing, and attitudes) from macro-scale factors (e.g., local labor and housing market conditions) for the same individuals. Therefore, they allow researchers to examine the separate contribution of covariates to current choices and behaviors and to predict the future of their regions. With a sufficient sample size of such panel surveys, researchers can lend support to planners and policymakers developing effective policies and programs that vary by sub-regional contexts (e.g., gentrified midtown versus redeveloped close-in suburbs).

6.4.1.2 Examine Housing Market and Local Business Trends with Urban Big Data

The growing availability, innovative use, and further development of new forms of urban "big data" provide researchers with unprecedented challenges and opportunities. Among these are new forms of online big data, those that are currently available *online* are relevant to the understanding and forecasting of the choices and behaviors of young age cohorts. After all, millennials are more responsive to information available from online sources (e.g., they search for rental units on apartments.com, trendy cafes or restaurants on Yelp, and bus/subway schedules on Google Maps). As conventional surveys collect key individual variables, researchers are able to enrich such variables with information from a variety of non-conventional sources. In the context of travel mode choice, a wide set of objective measures for level-of-service attributes can be extracted from open-source online services such as walkscore.com, the Center for Neighborhood Technology (alltransit.cnt.org), the Google Maps directions application programming interface (API), the general transit feed specification (GTFS), and the Open Street Map.

As for big data related to location choice, information on housing, business, and labor market conditions is available via commercial websites (e.g., Zillow.com, apartments.com, craigslist.com, Airbnb.com, infoUSA.com, schooldigger.com, and greatschools.org) and open-source API services (e.g., the Google Places API and Yelp.com). Information from these sources fills the gap in public data sources by providing highly geographically disaggregated data (i.e., many sources provide information with latitudes and longitudes) in greater detail, in real-time, or with frequent updates. Any trends found in the information from these sources are indicators of changing or non-changing local demand for transportation infrastructures and housing stock types. For example, residential property transaction data may reveal growing popularity for certain neighborhood attributes such as walkability and mixed land use. In short, incorporating urban big data of locational characteristics into survey datasets of individual attributes is desirable. After all, planners and policymakers will benefit from understanding not simply individual or environmental factors alone, but instead, the *interaction* between both.

6.4.2 Understand Heterogeneity within/across Generations

The main findings from the previous two sets of analyses in this dissertation are as follows: (1) Travel multimodality takes several forms, among which certain forms are more sustainable than others, and both conventional *and* attitudinal factors account for individuals choosing one form of travel multimodality over another; and (2) latent residential preferences are classified into several patterns, each of which presents unique tastes for particular neighborhood attributes, and individuals may switch from one set of preferences to another in response to life course events and changing attitudes. Thus, planners and policymakers are advised to estimate the composition (and its predicted changes in the near future) of latent classes among young adults in their regions. In other words, one-size-fits-all approaches (i.e., those based on the assumption that young adults are a homogeneous group) may not meet their heterogeneous demands for travel modes and types of neighborhoods and housing units and thus fail to promote sustainable travel behavior and development.

A seemingly simple question of "whether a region allows individuals, especially those who undergo transformative changes in their socioeconomic status and attitudes, to live *according to their preferences*" actually involves an understanding of the diversity of preferences and the ability of households to act on them. That is, planners need to know whether dense, mixed-use, or transit-rich urban neighborhoods in a region are unaffordable to those who *prefer* urban lifestyles or sustainable travel behavior, whether close-in suburbs are viable alternatives for those who *seek* both urban amenities and support for childrearing, and whether neighborhoods that young adults can afford to live in *allow* them to travel by alternative modes to nearby businesses and places for leisure activities. While not all individuals embrace the idea of sustainable development, it is the role of planners and policymakers to make such alternatives available and viable for those who *pursue* them. In doing so, estimations of the shares of latent classes in the population with varying lifestyles and preferences should provide planners and policy makers with critical information they need to make effective decisions.

6.4.3 Differentiated Approaches with Equity Perspectives

As for specific policies and programs that better serve the demand of today's young adults, planners and policymakers are advised to take *differentiated* approaches, each of which may appeal to one *latent* class but not to others, and also account for the equity implications of their approaches. First, to attract and retain young adults who want to reside in the central city, cities need to keep their urban amenities attractive, for example, by promoting mixed-use development, subsidizing local businesses, and improving the infrastructure for non-motorized travel in districts that gain popularity as venues for social, recreational, and cultural activities. Another critical factor that keeps young adult with children in the city instead of allowing them to move to suburbs is school quality. In addition, as young adults age and their households grow in size, they demand more square footage and settle down by buying homes. Thus, cities are advised to evaluate whether their land-use regulations are too restrictive (McCormick, 2017). After all, the supply of appropriate housing units, or lack thereof, affects the affordability of housing, and regulations controlling density, land-use mix, and lot sizes as well as inherent geographical constraints profoundly impact local housing markets.

As a result of the above factors, more and more cities have witnessed the attendance of "Yes In My Back Yard" (YIMBY) activists at public hearings and stronger support for projects such as multi-story condominiums mixed with commercial space. Architects and urban designers have also promoted the idea of "missing middle housing" as a solution for increasing residential density while preserving some aspects of the single-family home (Pearce, 2017; Shaver, 2017). After all, without a sufficient housing supply, an economically thriving region with a high quality of life (in part, because of educated young adults moving in and demanding more amenities) will price out less skilled workers and low-paying jobs (Kolko, 2018). The resulting imbalance among residents with varying income levels harms the sustainability of such regions because it leads to longer commutes by suburbanites, higher prices for basic services in the central cities, and segregation by income across communities.

If young adults have reason to choose to live in the suburbs (e.g., lower housing prices, higher quality schools, more square footage, and less crime) instead of the city, planners and policymakers may also wish to provide options that lie between the stereotypical urban and suburban neighborhoods. By doing so, they could meet latent demands for such hybrid neighborhoods and residents of such neighborhoods could reduce their vehicle use, if and when they choose to do so. As many urban scholars have pointed out, not all suburban neighborhoods are equal: Some are denser and interwoven with retail and service businesses with connected streets than others. As a result, planners have looked at close-in suburbs as an alternative for those who prefer urban amenities but who do not wish to sacrifice other housing and neighborhood characteristics (e.g., a spacious home, desirable school districts, and socioeconomically similar neighbors) (Economist, 2018;

Greenblatt, 2017). In fact, close-in suburbs, many of which were developed before World War II, are close to public transit facilities with relatively denser residential/commercial developments and street networks. Furthermore, by definition, these older suburbs are closer to the central city than their newer counterparts. Thus, to some extent, targeted approaches can help attract urban amenities to close-in suburban neighborhoods. Such approaches are to concentrate dense residential developments around old town centers or public transit facilities, support walkable districts with various types of local businesses, connect these businesses with infrastructures for non-motorized travel and natural amenities, improve access to the central city or suburban employment centers by public transit, and incentivize/mandate nearby employers to support non-motorized commuting (Clark & Greenfield, 2017; Kirkham, 2016; Wartenberg, 2014).

The recent urban revival in large metropolitan areas in the United States, catalyzed by the influx of college-educated young adults, has generated a growing concern over equity. Scholars and community activists have raised the following questions, among others: Does the urban revival price out low-income minorities from their communities in the central city? And if so, how can we justify policies and programs that favor one segment of the population, whose members are expected to bring in economic vitality via production or consumption to a region, at the expense of another segment, the voices of whose members have not been properly reflected in planning processes and outcomes in the past? Indeed, such policies and programs violate planning ethics. In addition, if planners fail to consider the implications of their approaches on those who most need their support, they will incur erosion of public trust. A recent defeat of Senate Bill (SB) 827 in California highlights the challenges planners and policymakers face in finding solutions to the dwindling housing supply while protecting the neighborhoods of the working class in the central city. Although SB 827 supported the densification of transit catchment areas in California, it failed to convince low-income minorities and support groups, including the Sierra Club, that the bill would not disproportionately harm the disadvantaged (Shneider, 2018). Planners and policymakers failed to pursue inclusive planning processes and outcomes, through which conflicting interests of stakeholders were evaluated and compromises and tradeoffs were made in a collaborative manner. The impact of school choice programs for existing households in a low socioeconomic status should also be examined so that their neighborhoods are not excluded from the benefits of such programs (Billings, Brunner, & Ross, 2018; Pearman & Swain, 2017). After all, planners need to work with education professionals to improve school quality and expand education options for residents in all income groups (H. S. Baum, 2004; Vincent, 2006).

6.5. Conclusion

The literature on the travel behavior of millennials, which has been growing rapidly, has two focuses: One is the determination of any significant differences between their travel demand and that of preceding birth cohorts; and the other is the identification of individual, environmental, and societal factors accounting for such differences. Nevertheless, the literature lacks rigorous analyses that foster an understanding among researchers and planners of the separate effects of various factors that could help them predict future travel and housing demand. After all, many studies in the literature (1) do not adopt a longitudinal framework, (2) they omit variables critical to a more comprehensive understanding of the reasons behind the behaviors and choices of millennials, and (3) they ignore the presence of heterogeneous groups in the millennial population, each of which exhibits distinct behavioral patterns and preferences. In response to these gaps in the literature, especially that related to the third point, this chapter presents a conceptual framework that illustrates the risk of adopting a one-size-fits-all planning approach to the demands of millennials. If planners and policymakers adopt such an approach, they will not only fail to meet the heterogeneous demands of the subgroups of millennials but also impede sustainable development and public transportation initiatives, thus discouraging those who are more flexible and responsive. In addition to the framework, this chapter summarizes key findings from the latent class location choice model of the previous chapter. The model identifies three latent classes in a sample of millennials in California: Young pro-urban, Affluent highly educated, and middle-class homeowners. It also shows that economic and demographic characteristics and attitudes of millennials determine their class membership. For instance, millennials in the high-income bracket or with children tend to belong to the Affluent highly educated class, but are less likely to be found among the Young pro-urban class. The perceptions of millennials towards car ownership and driving determine their residential preferences. Interestingly, the model also reveals a latent demand for urban amenities by suburban millennials.

Based on the conceptual and empirical investigation in this chapter, I present suggestions for future research and planning practices. One direction of research would be the collection of rich data with critical but often ignored information—attitudes and life course events—collected in a longitudinal study. A panel dataset is desirable, but the addition of retrospective questions to conventional regional travel surveys would also be valuable. Although not ideal, repeated cross-sectional analyses are more likely to reveal causality; however, they have not been implemented extensively in the millennial literature. Second, with data that include attitudes and life course events, we could examine the interactions of millennials and their effects on latent class membership. After all, understanding which latent classes are present in what shares of the millennial population of a region should guide planning efforts for infrastructure investments and land-use regulations.

From a practical perspective, this chapter supports three efforts: monitoring regional trends with growing availability of urban big data, acknowledging the presence and dynamic changes of latent classes in the population, and adopting targeted approaches with *equity* perspectives. As for equity concerns, planners and policymakers are advised not to favor millennials, an economically, demographically, and culturally active population, at the expense of vulnerable populations—minorities, low-income individuals, and those who have been less-represented in planning processes. To ensure effective efforts of regional governments, we need to enhance their understanding of travel behavior and the location choices of the current young population by research that models the interplay of attitudes, life course events, and latent class membership. The results of such research will inform planners and policymakers of the share (and longitudinal changes) of the latent classes in the regional population and advise them to meet the unique demands of millennials (and next generations) while promoting sustainable transportation and development.

CHAPTER 7. CONCLUSION

7.1 Millennials are on the Move

Millennials, those who were born from 1981 to 1996, present travel behaviors and mobility choices that differ from preceding generations at the same age. Since the late 2000s, millennials have been reported to postpone (or some of them appear to forego) the acquisition of a driver's license, own fewer cars on average, drive fewer miles, but instead more frequently use alternative modes such as walking, biking, and public transit. Academic studies and industry reports also find that, in part because they grew up with advanced information and communication technologies, millennials adopt emerging transportation services such as carsharing and ridehailing more than older cohorts.

Whereas many discussions depicting millennials as a *carless* generation abounded in the early 2010s, as the US economy has recovered from the economic recession since its trough in June 2009, the signs of millennials catching up with once-delayed life course milestones have appeared in society (e.g., working full-time or purchasing cars/homes). However, to this date the US still observe their trajectories in travel-related choices and outcomes to differ from those taken by preceding generations. Although on average, older millennials travel more miles by cars in 2017 than during the recession, substantial heterogeneity is present among them: those millennials in the low income bracket increased their car use noticeably, but the other millennials reduced it since 2009. The share of older millennials living in a car-free household has been larger than that of their predecessors, Gen Xers, even after the economic recession. Although fewer people have ridden public transit over time, millennials take more positive views on them, and their mode share of walking and biking increased substantially. New mobility solutions have been introduced to the market one after another (e.g., bike-sharing, car-sharing, ridehailing and scooter-sharing), and millennials are among early adopters or frequent users of those solutions, and as a result, many of them live without owning their own cars.

Studies and reports point to two factors behind these phenomena: changes in economies or cultures. Although the US has recovered from the recent recession, studies find that the recession still has lagging effects on wages, wealth, and household structures, and these effects appear to be larger for millennials than for preceding generations during the recovery periods from the past recessions. Moreover, the increase in educational attainment, later formation of an independent household and childbearing, and delayed homeownership are parts of long-term societal changes in the US in part because of intensifying competition under the global economy and transition to the knowledge-based economy. Last but not least, millennials are found to present values, views, and attitudes that differ from those of preceding generations. They take more pragmatic approaches to car ownership and driving, and they appear to be less materialistic but more supportive of environmental policies and active lifestyles. Also, with their experiences with advanced ICT solutions, they seem to choose virtual interactions instead of face-to-face counterparts with physical trips, and adopt emerging transportation services while not having their own vehicles. They are also claimed to prefer urban lifestyles or close proximity to urban amenities.

7.2 What do We Not Yet Know?

In this context, the academic and planning communities still lack an understanding of the fundamental relationships among various factors affecting the travel behavior and mobility/location choice of millennials. *First*, many studies analyze conventional household travel surveys that are readily available, but lack attitudes. Thus, their discussions are based on indirect reasoning, but not based on the estimates of the effects of attitudes. Although a few studies examined any generational differences in attitudes by conducting in-depth interviews and organizing group discussion sessions, in many cases their samples are small or not representative of the general population (e.g., cases were recruited by snowball sampling). *Second*, most studies examine various travel-related choices and outcomes separately but not in a comprehensive way. As for mode choice, less use of one mode may be compensated by more use of other modes; however, separate approaches cannot detect any trade-off behavioral patterns. Also, one of the fundamental choices that affect travel demand, location choice, has not been modeled properly in the literature. Instead, many studies modeled the built environment attributes as exogenous, which in fact are an outcome of a deliberate choice-making process. *Third*, with a few exceptions, the millennial literature does not examine the heterogeneity within and across generations. Given that millennials are the most diverse generation in the US history, it is reasonable to assume that they consist of several distinctive groups with heterogeneous behavioral patterns and preferences. To the extent that this hypothesis is true, the right question to ask is not whether millennials present different behaviors and choices *on average*, but in which forms and size heterogeneity is present among them and the preceding generations, and how likely these would change over time.

7.3 What Dataset Is Analyzed?

To address research gaps, in this dissertation I analyze a rich transportation survey dataset collected from millennials and members of Generation X (Gen Xers) in various parts of California in fall 2015 (N=1,975). Using quota sampling based on sociodemographic and economic characteristics, regions, and neighborhood types, the dataset include responses of members from less representative groups. The use of weights help reduce the non-representativeness of the sample when compared to the population in California. The survey consists of eleven sections including individual attitudes, residential location and living arrangements, work/study activities, current travel choices, driver's license and vehicle ownership, and sociodemographic traits. Out of 65 attitudinal statements, an exploratory factor analysis finds 18 attitudinal factors and 10 standalone statements, and after testing numerous combinations, this dissertation finds several factors appropriate for the explanation of millennials' behavior and choice. Moreover, for the reported home and workplace/school addresses, the built environment attributes from external sources, either from conventional or innovative sources, are appended to the dataset after geocoding, and another explanatory factor analysis generates three factors out of 33 attributes: amenities (i.e., close proximity to businesses and places for shopping/social/recreational activities), land-use mix, and development density. Below, as for the examination of heterogeneous modality styles, a subsample of the regular commuters (n=1,070) is employed, and as for that of heterogeneous residential preferences, a smaller subsample of the regular commuters with precise home and workplace/school addresses (n=729, after the exclusion of millennials living with parents) is analyzed; all analyses in this dissertation use the weighted dataset.

7.4 Modality Styles

With a latent-class cluster analysis, this dissertation analyzes the modality styles – defined as the patterns of monthly frequencies of using various travel modes – of millennials and Gen Xers in California, and presents five distinctive modality styles whose shares vary by generation, age group, and residential neighborhood type. Existing studies on multimodal travel behavior employ analytical approaches to the identification of multimodal travelers in ways that are simplistic or do not distinguish mode choice from longer-term mobility decision/commitment or outcomes. In comparison, this dissertation employs only the monthly frequencies of using various travel modes as indicators, and other travel-related variables either as active or inactive covariates (i.e., factors accounting for individuals choosing certain modality styles or factors used to show their outcomes in descriptive ways). The latent-class cluster analysis consists of two submodels that are simultaneously estimated: the measurement model that indicators enter to identify distinctive patterns of travel mode use on a monthly basis, and the membership model that individual socioeconomic/demographic characteristics and attitudes enter to account for their probabilities of belonging to unobserved groups, or latent classes, with heterogeneous modality styles.

This dissertation finds five modality styles: monomodal drivers (84.7%), active travelers (8.8%), multimodal drivers (2.9%), transit riders (2.3%), and multimodals for leisure (1.3%). Also, socioeconomics, demographics, attitudes, and inactive covariates of individuals help identify the characteristics of those belonging to each latent class. Not surprisingly, the majority of millennials and Gen Xers drive cars for most of their trips, although a smaller share of millennials belongs to the monomodal driver class. While findings are consistent with previous studies (e.g., monomodal drivers are the majority in the US), this dissertation reveals *several forms of multimodal travel patterns*, each of which is associated with a unique set of individual/household characteristics and built environment attributes. Interestingly, the multimodal for leisure class, whose members most frequently use emerging transportation services, consists of affluent and highly educated individuals who own their vehicles and drive as many miles as monomodal drivers, consistent with the small number of early adopters in the market in California in fall 2015. In short, each generation is not a homogeneous group in terms of modality styles but consists of five latent classes with distinctive modality styles. Also, their composition shifts gradually by age group and residential neighborhoods

With the understanding of the heterogeneous patterns of travel multimodality, this dissertation provides a couple of policy suggestions. Planners and policymakers affect built environment attributes by promoting/regulating certain types of developments in their neighborhoods/ regions. Dense neighborhoods with balanced land use and viable alternatives such as public transit allow young and older adults to travel by alternative modes especially when these individuals take positive attitudes. Also, leveraging the window of opportunity (e.g., for those recent movers during the period immediately after relocation) seems promising. When those with positive attitudes toward alternative modes relocate to those neighborhoods that support viable alternative transportation options, the provision of relevant information and incentives are expected to generate long-term effects by affecting their habit/routine formation process.

In this dissertation, I conduct a more rigorous analysis on mode use by taking into account trip purposes and emerging transportation services. While modality styles may take several forms, previous studies often describe them in either simplistic or less accurate ways (e.g., confused with mobility commitment or outcomes of various modality styles). Moreover, in this dissertation I account for the latent class membership with active and inactive covariates, and especially using a rich set of individual attitudes measuring various dimensions. In doing so, instead of estimating the average differences between members of two generations, in this dissertation I focus on the shifting shares of modality styles by age and residential neighborhood type. In addition, it suggests that the current multimodality styles of millennials most likely do not *entirely* disappear as millennials move to next life stages in part because attitudes will last longer than the demographic/economic conditions of millennials. Thus, investment in infrastructure for alternative modes will produce longer-term effects, if it is done with the *right* target population and in the appropriate areas.

7.5 Residential Preferences

With the highly disaggregate geography of home and work/school locations (measured at the Census block group) available in the California Millennials Dataset, this dissertation also examines heterogeneous residential preferences among a commuter subsample of millennials and Gen Xers (n=729). In doing so, it takes several approaches. First, it analyzes *revealed* preferences, not stated preferences under experimental choice settings or responses to Likert-scale attitudinal statements. In this dissertation, by residential preferences, I refer to the *coefficient estimates* of various attributes of alternatives in the choice set (e.g., the demographics, socioeconomics, and built environment attributes of Census block groups). Second, to deal with the problem of the missing information on the alternatives that individuals considered but did not choose (which are not observed in the data), in this dissertation I generate the choice set for individuals by randomly selecting block groups within an estimated search radius, i.e. a maximum acceptable commute distance, which differs by individual. For the estimation of the search radius, a survival model is employed with sociodemographic and economic characteristics of individuals as explanatory variables.

Third, a latent-class choice model (LCCM) is employed to explore the presence, type, and share of *heterogeneous* residential preferences in the sample. LCCM consists of two submodels that are simultaneously estimated: a choice model generates the coefficient estimates of various neighborhood attributes, which differ from one unobserved group (i.e., latent class) to another; and a membership model that measures the way individual characteristics and attitudes are associated with the likelihood of members to belong to each class. Last but not least, the attitudes of individuals on several dimensions (e.g., preferred neighborhood types, cars, and environmental policies) enter the membership model with their socioeconomic and demographic characteristics as the source of taste heterogeneity. By doing so, in this dissertation I examine the ways in which both socioeconomic/demographic conditions and *self-reported attitudes* of millennials and Gen Xers translate into revealed preferences under real, constrained choice situations.

This dissertation finds three latent classes with distinctive residential preferences: Younger, pro-urban (53%), Affluent, highly educated (32%), and Middle-class homeowners (15%). The members belonging to each class differ from those to the others by the way they derive utility from neighborhood attributes. The Younger, pro-urban class prefers block groups with higher shares of young adults (25-34 in 2015) and close proximity to businesses and places for shopping, social, or recreational activities, or rich urban amenities. The Affluent, highly educated class appears to value well-maintained neighborhoods, neighbors having high socioeconomic status, and affordability as an owner or renter. The members of the Middle-class homeowner class tend to choose neighborhoods with well-performing public school, affordable homes for owners, and mixed land-use patterns.

The individual-level profiles of these latent classes are consistent with their revealed residential preferences. Many members of the Younger, pro-urban class are millennials (under 35 in 2015), or living in the central city or urban neighborhoods. They live with a more number of a child under 6 than the other classes on average, study full-time or part-time more, but work less than the other classes, earn lower incomes, own homes less, and take more positive attitudes toward urban lifestyles and environmental policies that regulate the use of cars. More than a half of the Affluent, highly-educated class earned the Bachelor's degree, and additional 30% a graduate degree. 90% of them work full-time, and 42% make household incomes more than $120,000 a year. Although members of this class are wealthier than those of the others, only 60% of them own homes, suggesting that they tend to choose lifestyles or high socioeconomic status of neighbors over home ownership or the quality of schools. The middle-class homeowner present the largest share (61%) of those households making incomes in the middle range, between $60k and $120k, and 90% of them own homes. The members of this class have the largest likelihood of having a child from 12 to 17 in the household, on average, which explains their preferences for good neighborhood schools. With budget constraints and demand for well-performing schools, it is understandable that three fourth of this class lives in suburban or exurban neighborhoods.

A further examination of the differences in the share of the three latent classes by generation, age group, and residential neighborhood type confirms that on average more millennials (and urban residents) are found among the Younger, pro-urban class. However, this dissertation also demonstrates that millennials and Gen Xers consists of three distinctive groups with heterogeneous residential preferences and that *both* demographic/economic characteristics *and* attitudes account for individuals presenting such heterogeneous preferences: e.g., not all millennials pursue urban lifestyles, and not all households with high incomes or a school age child relocate to suburban neighborhoods.

This dissertation finds the presence of unobserved groups in the population, whose members present heterogeneous residential preferences and differ by *both* socioeconomic and demographic characteristics *and* attitudes. Based on the findings and understanding so obtained, I suggest several policy implications and future research directions. First, it is of critical interest to planners and policymakers to identify latent classes in their region and examine the extent to which the various types of neighborhoods and transportation infrastructures are available or affordable in the region. Second, this dissertation highlights the latent demand of suburban residents for urban amenities and infrastructure for alternative modes, especially among those who prefer urban lifestyles for affordable housing and quality schools. Third, the probabilities of individuals belonging to latent classes can be used for the identification of consonant/dissonant residents, who may present different patterns of travel demand, satisfaction, and subjective well-being.

This dissertation contributes to the millennial literature in two ways. While the current discussion on the residential choice of millennials tend to take sides between two narratives, “back-to-the-city” or “secretly-buying-in-suburbs”, this dissertation models taste heterogeneity among millennials and Gen Xers and presents the varying compositions of latent classes by generation, age group, and neighborhood types. It also examines the ways individual characteristics and attitudes account for their probabilities of belonging to one latent class or another. The profiles of each class and the membership model outcomes generate insights on the possible ways in which individuals may shift from one class to another in response to any change in life stages or attitudes.

7.6 Future Research Suggestions and Planning Implications

Based on the findings and understanding obtained from the analyses of heterogeneous modality styles and residential preferences, this dissertation suggests several directions for further research and implications for planning and policy. Regarding the next research steps, individual-level panel with attitudes and life course events are of critical importance because such data allow dynamic modeling of the behavior and choice of young adults, which identifies the unique contributions of various factors: e.g., with such data, researchers can examine the separate or interactive effects of life course events, attitudes, and latent class membership of individuals. Given that most studies analyzed repeated cross-sections in the millennials literature, panel analysis will contribute to the understanding of longitudinal (causal) relationships of diverse factors and the behavior and choice of millennials, many of whom are in their formative years.

Regarding planning and policy, the monitoring of regional trends in travel behavior and location choice is necessary. As this dissertation demonstrates, modality styles and revealed residential preferences are not only the choice of individuals based on sociodemographic, economic, and attitudinal characteristics but also their (strategic) response to available transportation infrastructure and local housing markets. In this sense, latent-class approaches help explore the spatial distribution of unobserved groups with varying modality styles and residential preferences, with which land-use, housing, and transportation planners identify any discrepancy between supply and demand and customize approaches that best meet local and regional demand. For urban neighborhoods, further densification around public transit facilities or employment centers, open enrollment policy for public schools, and investment in infrastructures for active modes will retain those millennials who pursue urban lifestyles. For suburbs, the provision of rich consumption amenities around the old own centers of inner-ring suburbs or regional transit facilities will meet the latent demand of some suburbanites for urban lifestyles, while allow them to reduce dependence on private cars. Last but not least, planners and policymakers also need to examine any systematic pattern in the exclusion of the disadvantaged or vulnerable population from the benefits of policy and incentives that meet the unique demand of millennials and promote sustainable developments and travel behavior. After all, while the aforementioned approaches for urban neighborhoods indeed attract young adults, they often favor new movers at the expense of existing residents, who often differ substantially in their socioeconomic status.

7.7 Limitations

This dissertation has several limitation. First, it analyzes a cross-sectional dataset collected in fall 2015, so it cannot accurately estimate cohort effects. That is, instead of comparing millennials with Gen Xers at the same age, this dissertation compares millennials under 35 with Gen Xers who were 35 or older in 2015. For instance, although sociodemographic, economic, and attitudinal characteristics of individuals are controlled for in this research, Gen Xers in their 40s may not be the right target group for the comparison with millennials in the 20s. Thus, the outcomes and findings of this dissertation need be considered as based on temporary variation within young and older adults at a given time point, which does not necessarily translate into differences between generations. In this sense, a follow-up study that focuses on a subgroup of the California Millennials Dataset, those born from 1976 to 1985 (*i.e.*, those in the 30s in 2015), may generate fresh insights on generational effects. Note that the age gap within this subgroup is not substantial, but those born in the first five years (1976-1980) are classified as Gen Xers, and those in the last five years (1981-1985) as millennials. Thus, if *age* (or a binary indicator denoting whether individuals are millennials or Gen Xers) presents significant effects on modality styles or residential preferences all else being controlled for (sociodemographic, economic, and attitudinal characteristics), we may be able to interpret its effects as those of specific cohorts.

Other limitations are: the two analyses in this dissertation are not a *joint* estimation of location choice, mobility decision (*e.g.*, car/bicycle ownership, the acquisition of driver's license, or the possession of transit pass), and travel behavior. Moreover, although measuring a comprehensive set of variables, the California Millennials Dataset lacks a few variables that may be of critical importance to the understanding of behavior or choice of millennials: for example, it does not ask detailed financial situations such as the total amount of debt for student loans or monthly payments. Although the dataset contains life course events happened in the last three years including residential relocation, graduation, job change, marriage, and childbearing, it does not ask past experiences that may have happened more than three years ago (*e.g.,* age at which an individual first started to work).

In addition, the definition of independent millennials, i.e. living without parents, may not properly determine the economic independence of millennials in certain situations (*e.g.*, millennials living with relatives in their home or millennials whose parents help them to buy homes (H. Lee, Myers, Painter, Thunell, & Zissimopoulos, 2018)). While location choice is a household-level decision, attitudes, which enter the membership model, may vary by individual in the same household. Last but not least, in this dissertation I analyzed a dataset collected in 2015, and the modality styles and residential preferences of young and older adults may have changed since then *partially* in response to the economic recovery after 2009 and the evolving market for emerging transportation services.

7.8 Concluding Remarks

Will millennials stay in cities and travel without cars? To answer this question, in this dissertation I examine heterogeneity in modality styles and residential preferences in a sample of young and older adults in California in 2015. In doing so, I also find that *both* sociodemographic/economic characteristics *and* attitudes on various dimensions account for the heterogeneous behavioral and choice patterns of millennials and Gen Xers. These findings provide insights on the ways millennials may switch their modality styles or residential preferences in response to changes in demographic/economic conditions or attitudes in coming years. I also confirm the role of the built environment that allows individuals to use alternative modes (or prevents them from doing so), and the existence of latent demand for affordable housing and quality public schools in cities and for urban amenities in suburbs.

This dissertation highlights the use of latent-class approaches as effective for the identification of taste heterogeneity in the context of travel behavior and location choice of millennials. Researchers are advised to apply these approaches to longitudinal analysis, and planners and policymakers need be informed of the dynamic changes in the form or share of latent classes with heterogeneous tastes and demand for housing, neighborhood, and transportation infrastructure, which are specific to their region. It is interesting to note that, while the majority of the commuter sample (85%) in this dissertation drive most of time, a sizeable portion of commuters (53% of a smaller commuter sample) prefer rich consumption amenities in their neighborhoods. This signals that there is a window of opportunity associated with those who prefer multimodality or urban lifestyles. Planners and policymakers should leverage the unique preferences and demand of these dynamic millennials to promote sustainable developments and transportation. "A big shift in travel behavior won't happen without big shifts in policy."(Schmitt, 2017)

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